Technical Report 12-006

Social Network Analysis in Frontier Capital Markets

Daniel Evans
Margaret Moten
Csilla Szabo
Brian Macdonald

U.S. Military Academy, West Point NY

June 2012

United States Military Academy
Network Science Center

U.S. Military Academy
Network Science Center

Authorized and approved for distribution:

BG (R) CHRIS ARNEY, Ph.D.	**COL JOHN M GRAHAM, Ph.D.**
Network Science Chair	**Director, Network Science Center**

Technical review by

MAJ Anthony Johnson, Ph.D., Department of Mathematical Sciences, U.S. Military Academy
Charles Thomas, Ph.D., Department of History, U.S. Military

NOTICES

DISTRIBUTION: Primary distribution of this Technical Report has been made by the U.S. Military Academy Network Science Center. Please address correspondence concerning distribution of reports to: Network Science Center, U.S. Military Academy, 646 Swift Road, West Point, NY 10996

FINAL DISPOSITION: This Technical Report may be destroyed when it is no longer needed. Please do not return it to the U.S. Military Academy Network Science Center.

NOTE: The findings in this Technical Report are not to be construed as an official Department of the Army position, unless so designated by other authorized documents

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
20-06-2012

2. REPORT TYPE
Technical Report

3. DATES COVERED *(From - To)*
June 2010-May 2012

4. TITLE AND SUBTITLE
Social Network Analysis in Frontier Capital Markets

5a. CONTRACT NUMBER
n/a

5b. GRANT NUMBER
n/a

5c. PROGRAM ELEMENT NUMBER
n/a

6. AUTHOR(S)
Daniel Evans, Margaret Moten, Csilla Szabo, and Brian Macdonald

5d. PROJECT NUMBER
ARO NetSci 02

5e. TASK NUMBER
n/a

5f. WORK UNIT NUMBER
n/a

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Network Science Center,
U.S. Military Academy
601 Cullum Road, Thayer Hall Room 119
West Point, NY 10996

8. PERFORMING ORGANIZATION REPORT NUMBER
n/a

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
U.S.Army Research Office
Triangle Park, NC

10. SPONSOR/MONITOR'S ACRONYM(S)
USMA NSC

11. SPONSOR/MONITOR'S REPORT NUMBER(S) 12-006

12. DISTRIBUTION / AVAILABILITY STATEMENT
Unlimited Distribution

13. SUPPLEMENTARY NOTES
The views expressed in this thesis are those of the authors and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

14. ABSTRACT
The study of frontier capital markets provides a unique opportunity to examine the network-based intersection of human behavior and economics. The individual motivations, information availability, transaction systems, and cultural realities in these markets provide a rich context of study. A social network analysis reveals interesting insights about how interrelationships among actors and organizations affect market operations and development. Network analysis provides both a visual and mathematical representation of the relationships and information flows between people, organizations, and functions, enabling one to describe capital market structure and function in innovative ways. This research focuses on the capital markets in three frontier markets, Ghana, Tanzania, and Trinidad and Tobago, providing insights to economists seeking to understand the interconnections between economic actors and their affects on financial markets and economic conditions. Data collection challenges resulted in models that may be incomplete. However, this analytic approach and the unique methodology for data collection can be used by researchers in the fields of economics and network sciences and may be applicable to other types of real-world, complex datasets.

15. SUBJECT TERMS
Social Network Analysis, Network Science, Economics, Capital Markets, Frontier Markets

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	UL	42	Tish Torgerson
					19b. TELEPHONE NUMBER *(include area code)* 845-938-0804

Technical Report 12-006

Social Network Analysis in Frontier Capital Markets

Daniel Evans
Margaret Moten
Csilla Szabo
Brian Macdonald

U.S. Military Academy, West Point NY

U.S. Military Academy Network Science Center
601 Cullum Road, Thayer Hall Room 119, West Point, NY 10996

20 June 2012

ACKNOWLEDGEMENT

This work was supported by the U.S. Army Research Organization, Project No. 1JO1XR059 and 1FO91XR029.

Daniel Evans supports this project through the Army Research Office's Scientific Support Program. Battelle Memorial Institute administers the Scientific Support Program for the Army Research Office.

Social Network Analysis in Frontier Capital Markets

Daniel Evans, Margaret Moten, Csilla Szabo, Brian Macdonald

May 14, 2012

Abstract

The study of frontier capital markets provides a unique opportunity to examine the network-based intersection of human behavior and economics. The individual motivations, information availability, transaction systems, and cultural realities in these markets provide a rich context of study. A social network analysis reveals interesting insights about how interrelationships among actors and organizations affect market operations and development. Network analysis provides both a visual and mathematical representation of the relationships and information flows between people, organizations, and functions, enabling one to describe capital market structure and function in innovative ways. This research focuses on the capital markets in three frontier markets, Ghana, Tanzania, and Trinidad and Tobago, providing insights to economists seeking to understand the interconnections between economic actors and their affects on financial markets and economic conditions. Data collection challenges resulted in models that may be incomplete. However, this analytic approach and the unique methodology for data collection can be used by researchers in the fields of economics and network sciences and may be applicable to other types of real-world, complex datasets.

Contents

1 Introduction

Economic research has recognized that well-functioning financial markets are associated with economic growth[1]. However, the basic assumptions underlying macro-economic and financial theory are increasingly subject to debate including rational expectations, representative agent, and efficient markets theories. Economic research focused on modeling the behavior of networked, diverse economic agents is emerging to address limitations in traditional economic theoretical foundations.

Understanding the structure, dynamics, and unique characteristics of the capital market network in which individuals operate is vital to analyzing how capital markets evolve, especially in developing economies where individuals make reciprocal exchanges and clan or family interests are as important as individual self-interest or social norms, institutions and legal frameworks. Our network approach reveals existing qualities of market behavior that do not adhere to traditional economic assumptions providing insights to the study of network science, economics, and capital markets.

1.1 Limitations of Traditional Economic Theory

The rational expectations theory, one of the cornerstones of financial economic theory, posits that individuals incorporate all available information when developing expectations and that prices today are a function of the individual's expectations about the future. Built

[1]Levine and Zevros found that developed capital markets are correlated with improved economic performance and there is a link between the size and liquidity of stock markets and easy access to information, rigorous accounting standards, and strong investor protections. See [LZ96].

upon the rational expectations theory, Fama's efficient markets hypothesis asserts that a security's price reflects all the company and market information that is available [Fam70]. Economic theorists, including John Maynard Keynes, have argued that perfect information and the rational man are idyllic concepts.

Moreover, the collapse of the financial system in 2007 highlights the shortcomings of the representative agent approach and the dangers of failing to incorporate financial networks and their affects on risk and contagion. Economic research focused on modeling the behavior of networked, diverse economic agents is emerging to address limitations in traditional economic theoretical foundations.

Kirman [Kir10] argues that individuals don't behave according to microeconomic principles and aggregation is a problem. "The homo economicus is not an accurate or adequate description of human decision making." He further questions assumptions such as representative agent, stability and uniqueness of equilibria, individual rationality, information availability, and an anonymous market. The recent financial crisis offers a bleak illustration. Financial institutions acting individually to maximize their returns and minimize risk spread increasingly complex financial instruments (that were little understood) throughout the financial system thereby destabilizing it. The highly interdependent network of financial institutions that evolved was not predicted or explained by economic models, resulting in the near collapse of the entire system. Kirman suggests that macroeconomic theory needs to incorporate the network of interacting individuals, the structure of their interactions, and the consequences of network activity [Kir10].

Stiglitz and Gallegati [SG11] introduced new heterogeneous agent models to enhance our understanding of macro-economic behavior. Their model incorporates credit markets, credit linkages, and risks of bankruptcy because an increase in credit defaults leads to higher interest rates which increases the risk of additional borrower defaults and financial institution collapse. "In the real world, idiosyncratic shocks can well give rise to aggregative consequences; such shocks can be the source of an 'epidemic,' giving rise to financial distress, the effects of which diffuse throughout the economy, and can often translate into a contraction of real GDP. In other words, in a financial network idiosyncratic shocks usually do not cancel out in the aggregate, especially if a shock hits crucial nodes (hubs) of the network. Studying when that can be the case - and how the structure of the network affects the aggregate impacts - should be a prime focus of macroeconomic analysis"[SG11].

The majority of the previous study involving network analysis and economics has focused on micro-economic theory with a general emphasis on decision-making, individual behavior, and game theory. Network scientists have delved into such topics as viral marketing and the economics of network-valued commodities, but increasingly researchers are recognizing the need to incorporate a network approach to enhance our understanding of macro markets. Individuals make economic decisions in a market context that is influenced by their social interactions and opportunities. Economic analysis and prediction is further complicated in developing economies where individuals make reciprocal exchanges and clan or family interests are as important, or maybe more important than individual self-interest. Other important considerations are the social norms, institutions and legal frameworks within which individuals operate. Furthermore, information asymmetry and insufficient contract enforcement can limit the willingness of creditors and investors to provide critical investment funds. We expect our network approach to discover existing qualities of market behavior that do not adhere to traditional economic assumptions. This research is important not

only because of the insight it gives to the study of network science, but also because of the understanding it provides about economics and capital markets. Network analysis can broaden our understanding of the critical factors affecting market development.

1.2 Frontier Market Networks

Financial analysts classify capital markets as developed, emerging, or frontier. We focus on frontier markets, the smallest, less developed, less liquid investable markets. In these capital markets, social connections play a much more critical role than in developed capital markets. Functioning capital markets enable developing economies to attract domestic and international investment needed to support entrepreneurs, expand economic opportunities, and foster economic growth. Frontier markets have smaller scope and fewer institutional controls, and social relations and human behavior have a greater impact. Thus, the study of frontier capital markets provides a unique opportunity to examine the network-based intersection of human behavior and economics. The individual motivations, information availability, transaction systems, and cultural realities in these markets provide a rich context.

1.3 Capital Markets and Development

Well-functioning capital markets are an extremely important component of capitalism. Companies require funds to expand, develop new products and services, and construct facilities. Governments use capital market funding to develop infrastructure, for government projects and initiatives, and deficit financing. Few foreign investors participate in a frontier or emerging market unless they know they can sell their shares easily in well-regulated markets. Investors require transparency, as well as reliable financial and management information. Government stability, economic policies, taxation, and the ability to repatriate capital can also influence an investor's risk perception. Successful economic development also requires that local entrepreneurs have access to the capital necessary for business expansion, but little is understood about the types and functions of capital markets in the world's less-developed countries.

1.4 Capital Market Network Analysis

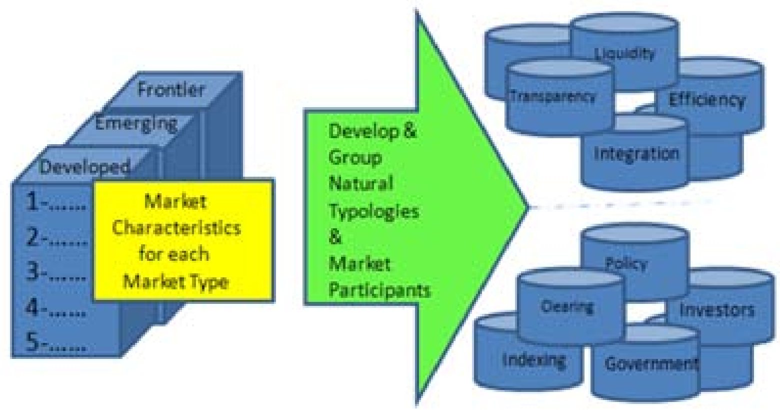
Network analysis can inform behavioral, financial and development economists seeking to understand the essential characteristics that foster capital market development in countries where social capital can be as important as financial capital. As Stiglitz and Gallegati [SG11] note, "Some network designs may be good at absorbing small shocks, when there can be systemic failure when confronted with a large enough shock. Similarly, some typologies may be more vulnerable to highly correlated shocks." Goyal [Goy07] found that, "Network structure has significant effects on individual behavior and on social welfare." He concluded that some networks are better than others to promote socially desirable outcomes, and both the quality and quantity of the links in the networks are important.

1.5 Analytic Approach

A social network analysis reveals interesting insights about how interrelationships among actors and organizations affect market operations and development. Network analysis pro-

vides both a visual and mathematical analysis of the relationships and information flows between people, organizations, and knowledge entities enabling us to describe capital market structure and function in innovative ways. Our initial research focuses on the capital

Figure 1: Study Concept



markets in three frontier markets: Ghana, Tanzania and Trinidad and Tobago. We collected extensive data about the actors in the markets using mathematical techniques to identify and evaluate the nodes in the network. Initially focusing on stock exchange personnel and government regulators, we expanded the network to encompass public companies, banks, brokers, and key personnel in government.

We recorded individual résumé data including the businesses, clubs and professional associations with which they were associated. We documented nationality, educational attainment and university affiliations, and conducted interviews with key "nodes" at the stock exchanges, banks, brokerage firms, and government organizations.

Using Organizational Risk Analyzer (ORA) a network analysis software developed by the Center for Computational Analysis of Social and Organizational Systems at Carnegie Mellon University [ORA], we constructed social networks for each country's capital markets depicting how agents and organizations are affiliated, calculated network metrics, and generated network topologies. A person is linked to an organization if one (or more) of the following is true:

1. the person is currently, or was previously, employed by an organization
2. the person currently or previously served on the board of directors of an organization
3. the person attends or attended a college or university

Using relational and matrix algebra, we created two networks for each country. The first network is an agent-to-agent network where the nodes are agents and two agents have a link between them if they share a common organization. The other network is an organization-to-organization network where the nodes are organizations and two organizations have a link between them if they share a common agent.

We then generated network measures and topologies of all of these networks and identified which agents and organizations serve as central hubs and power brokers. We also noted

the nodes on the shortest paths between nodes that exhibit the most influence on other nodes. These network topologies enable us to classify, compare and contrast capital market networks.

2 Node Level Measures

Node centrality measures are defined for each agent in a network that aim to quantify how central or influential that agent is in the network. One could have different ideas about what it means to be "central" or "influential" depending on the question one is trying to answer about an agent or a network; there are centrality measures for many of these ideas. For example, one might consider an agent "central" if the agent is connected to many other agents. This idea motivates the definition of *degree centrality*. Here we briefly introduce four centrality measures: degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality, and describe the attributes of agents that rank high in these centrality measures. A good reference for a more detailed discussion of centrality is the book *Social Network Analysis* by Wasserman and Faust. See [WF94].

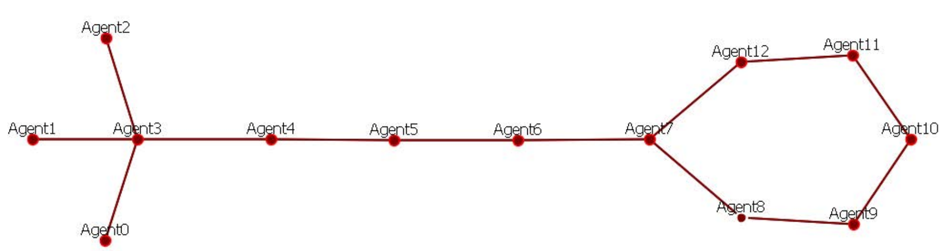
2.1 Degree Centrality

Degree centrality is based on the idea that an agent is important or influential if the agent is linked to many other agents. An agent with high degree centrality may have the opportunity to directly influence many other agents in the network. Suppose agent k is connected to d_k other agents. The *degree* of agent k is d_k, and the degree centrality of agent k is the degree normalized by the number of agents in the network that could be connected to agent k. If the network has N nodes, then at most $N-1$ agents could be connected to agent k, and the degree centrality of agent k, denoted, C_{D_k}, is

$$C_{D_k} = \frac{d_k}{N-1}.$$

See the example network in Figure 2. In that network, there are $N = 13$ nodes, and each

Figure 2: A Sample Network



node could be connected to at most $N-1 = 12$ other nodes. Agent3 is connected to 4 other nodes and has a degree centrality of

$$C_{D_3} = \frac{d_3}{N-1} = \frac{4}{13-1} = \frac{4}{12} = \frac{1}{3} \approx 0.333.$$

Agent0, Agent1, and Agent2 are only connected to one node, Agent3, and have degree centrality $1/12 \approx 0.083$. Table 1 contains comparative measures of centrality for selected nodes used to develop the sample network in Figure 2.

Table 1: Degree, Betweenness, and Closeness Centrality for some nodes in Figure 2.

Agent	Degree	Closeness	Betweenness	Eigenvector
Agent3	0.333	0.286	0.455	0.507
Agent6	0.167	0.364	0.545	0.456
Agent7	0.250	0.353	0.561	0.599
Agent5	0.167	0.353	0.530	0.397
Agent4	0.167	0.324	0.485	0.413
Agent0	0.083	0.226	0.000	0.232

2.2 Closeness Centrality

Closeness centrality is a measure of how close each node is to other agents in the network. An agent with a high closeness centrality is often considered to have indirect power in the network. To give the precise definition of closeness centrality, we first need to define a couple of terms. A *path* is a alternating sequence of nodes and links, which starts and ends with a node, and where each link connects the node before it to the node after it. A path can be described by listing only the nodes in the path. For example, the path

$$\text{Agent8} \rightarrow \text{Agent9} \rightarrow \text{Agent10} \rightarrow \text{Agent11} \rightarrow \text{Agent12} \tag{1}$$

is the path between Agent8 and Agent12 that passes through Agent9, Agent10, and Agent11.

The *length* of a path is the number of links in that path. For example, the path described in (1) has length 4. A *geodesic* between two nodes is the shortest path between those two nodes, meaning the path of minimum length. The path in (1) is not a geodesic, because there is a shorter path between Agent8 and Agent12, namely the path Agent8 $\rightarrow$ Agent7 $\rightarrow$ Agent12 (see Figure 2). This path has length 2 and the path is a geodesic because all other paths have length more than 2. Finally, the distance between node j and node k, denoted $\text{dist}(j, k)$, is the length of a geodesic between them. For example, $\text{dist}(\text{Agent8}, \text{Agent12}) = 2$.

The closeness centrality of agent k is computed by first finding average distance between agent k and all of other agents. The average distance is computed by finding the sum of the distances between k and the other nodes, and dividing by $N-1$, the number of other nodes in the network. For Agent0 we have

$$\frac{1}{N-1}\sum_{k=1}^{12} \text{dist}(\text{Agent0}, \text{Agent}k) = \frac{1}{12}\Big(2+2+1+2+3+4+5+6+7+8+7+6\Big) = \frac{53}{12}.$$

The closeness centrality is the reciprocal of the average distance. For example, the closeness centrality of Agent0 is

$$\frac{1}{53/12} = \frac{12}{53} \approx 0.226.$$

See Table 1 for the closeness centrality for some of the nodes in the network. Agent6 is the highest in closeness centrality, indicating that Agent6 may have a lot of indirect power in the network.

Each of the agent and organization networks we consider are disconnected, meaning there does not exist a path between each pair of nodes. Because the network is disconnected the closeness centrality values are either very high or very low due to the distances in the calculation. For our analysis of the networks we will examine the largest connected component for the closeness centrality measures.

2.3 Betweenness Centrality

Betweenness centrality is based on the idea that an agent is important or influential in some way if the agent lies on paths between two other agents. Agents with a high betweenness centrality could be considered to be like gatekeepers, or the agents who control the flow of information in a network.

Betweenness centrality of an agent in a network is based on the number of geodesics on which that agent lies. If a node has high betweenness centrality, then several geodesics will contain that node. As mentioned before, nodes with high betweenness centrality are often thought of as gatekeepers, or nodes that control the flow of information, because they lie on several geodesics. They may also be considered bridges that span disconnected groups. Calculating betweenness centrality is rather tedious to do by hand and is best left for a network analysis software package like ORA [ORA].

The betweenness centrality for some nodes in the network in Figure 2 is listed in Table 1. Note that three different nodes are the highest in the three different centralities. Agent3 has the highest degree centrality, while Agent6 has the highest closeness centrality, and Agent7 has the highest betweenness centrality. Also, note that Agent0 has a betweenness centrality of zero since it does not lie on any geodesics between other nodes.

2.4 Eigenvector Centrality

Eigenvector centrality is a measure of how connected a node is to influential nodes. A central node that is connected to other central nodes will tend to have a high eigenvector centrality. Eigenvector centrality is computed by finding the eigenvalues and eigenvector of the adjacency matrix of the network. The eigenvector centralities of the nodes in the network are the entries of the eigenvector that corresponds to the largest eigenvalue of the adjacency matrix. For more information about eigenvalues, eigenvectors, and related topics like principal components analysis, see, for example, a standard linear algebra text like [Bre09], [Str88], or [Lay06].

3 Network Level Measures

The node level measures discussed previously allow us to analyze individual nodes and gain insights about their influence, connectedness, and relative power in the network. Network level measures enable researchers to evaluate each network as a whole and then compare and contrast it with other networks.

3.1 Density

The density of a network is the ratio of the number of links present in the network to the number of possible links in the network [WF94]. For a network with N nodes, there are $\binom{N}{2} = \frac{N(N-1)}{2}$ different pairs of nodes, and therefore $\frac{N(N-1)}{2}$ possible links. If this network has L links, then the density, D, is

$$D = \frac{L}{(N(N-1)/2)} = \frac{2L}{N(N-1)}.$$

For example, in the agent-to-agent Ghana network (described in Section 4), we have 289 nodes representing the people or agents in the network. There are 2939 links out of $\binom{289}{2} = \frac{289 \cdot 288}{2} = 41,616$ possible links, giving us a density of 0.0706.

In recent work of Liu, Slotine, and Barabasi [LSB11], the authors study controllability of networks. One of their findings is that networks that are more dense seem to be easier to control, and networks that are less dense seem to be harder to control.

3.2 Diameter

The diameter of a network is the longest geodesic or longest shortest path between two nodes. It gives the farthest distance that exists between any two nodes in the network. If we consider information or messages traveling through the network, the diameter gives an upper bound for the time required for the message to reach all nodes [WF94].

3.3 Diffusion

The diffusion of a network measures how easily something like information or an idea can spread through a network. A network with a small diffusion value has nodes that are far apart and information or ideas tend to diffuse slowly. A large diffusion value in a network indicates nodes are relatively close together and information or ideas diffuse more quickly.

3.4 Degree Distribution

The degree distribution of a network is the relative frequency distribution of the number of nodes to which each node is connected. A degree distribution is often depicted using a histogram indicating various degrees, or ranges of degrees, along the horizontal axis and the proportion of nodes in the network that have each degree along the vertical axis. Figure 3 contains an example of the degree distribution of our agent-to-agent network for Ghana. Most of the nodes have a degree between 1 and 40, while only 4 nodes have a degree greater than 85. Degree distribution histograms for the agent-to-agent networks of Tanzania, Ghana, and Trinidad and Tobago are given in Figures 7 to 9, and degree distribution histograms for the organization-to-organization networks of Tanzania, Ghana, and Trinidad and Tobago are given in Figures 19 to 21.

Some degree distributions naturally arise often enough that they are given a name. An example of one of these distributions is the power law distribution, which is defined as follows. Suppose $f(n)$ denotes the number of nodes of degree n. If $f(n)$ is approximately proportional to $\dfrac{1}{n^b}$ for some $b > 0$, then $f(n)$ follows a power law distribution. In other

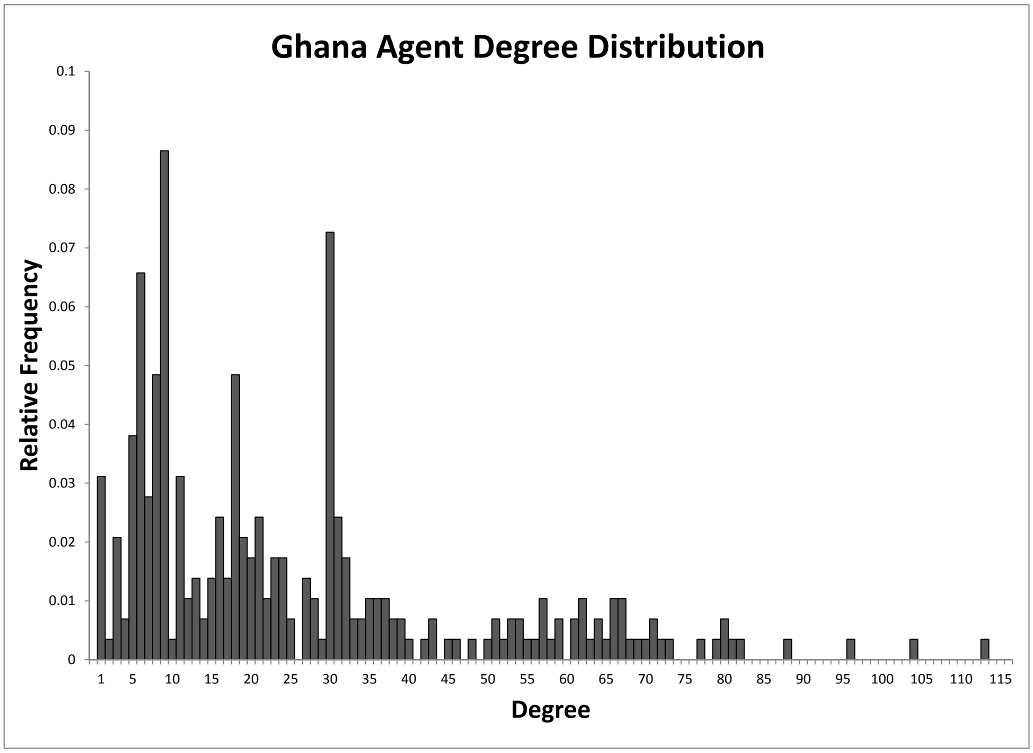


Figure 3: Degree distribution for Ghana's agent-to-agent network.

words, we could say that $f(n)$ follows a power law distribution if

$$f(n) \approx \frac{a}{n^b} \tag{2}$$

for some constants $a > 0$ and $b > 0$.

Functions of the form $\frac{a}{n^b}$ are large for small values of n and decay quickly as n increases. Networks that follow a power law distribution tend to have several nodes of low degree and few nodes of high degree. An example of this kind of distribution is given in Figure 4, where we give the degree distribution of the organization-to-organization network for Tanzania. In fact, the organization-to-organization networks of all three countries follow a power law distribution (see Figures 19 to 21).

One way to visually investigate whether or not a degree distribution follows a power law distribution is to plot the degree distribution using logarithmic scales on both axes. This kind of plot is often called a log-log plot. If the degree distribution is a power law distribution, then the log-log plot will be approximately a straight line. We can see why this is by taking the log of both sides of (2), which gives us

$$\log f(n) = \log \frac{a}{n^b}. \tag{3}$$

Using the fact that $\log \frac{c}{d} = \log c - \log d$, we can write (3) as

$$\log f(n) = \log a - \log n^b. \tag{4}$$

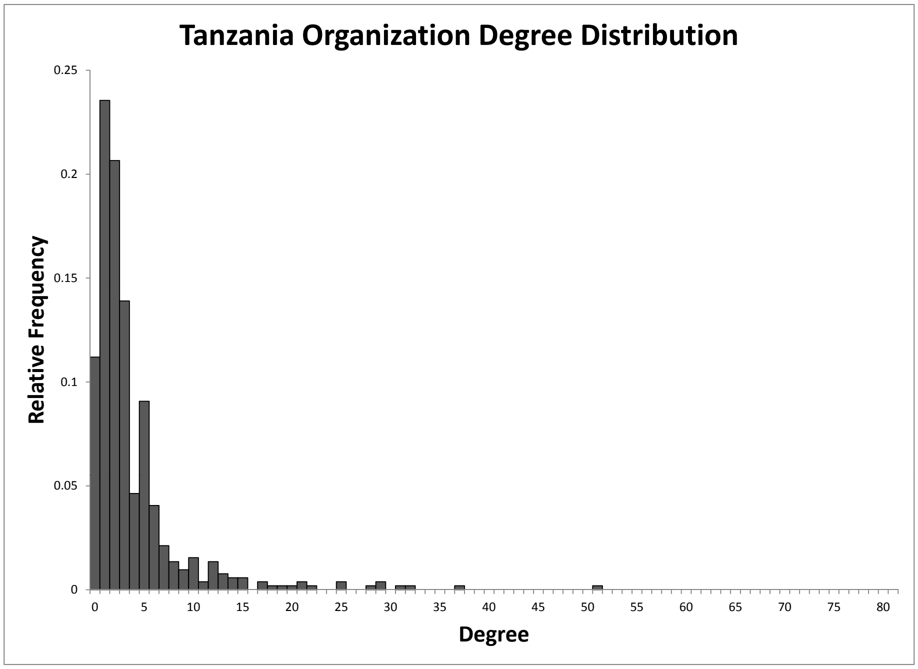


Figure 4: Degree distribution for Tanzania's organization-to-organization network.

Finally, using the fact that $\log c^d = d \log c$, we can write (4) as

$$\log f(n) = \log a - b \log n. \tag{5}$$

If we write $y = \log f(n)$ and $x = n$, we get

$$y = \log a - b\, x$$

or

$$y = -bx + \log a,$$

which looks like the slope-intercept form of a line with slope $-b$ and intercept $\log a$.

So on a log-log plot, the degree distribution looks like a line with a slope of $-b$ and an intercept of $\log a$. In Figure 5, we give the log-log plot of the degree distribution of the organization-to-organization network for Tanzania. Note that the data points are roughly along a straight line.

3.5 Fragmentation

The fragmentation measure considers the number and size of components or pieces of a network to give a proportion of nodes that are disconnected in a network [Bor03].

3.6 Clustering Coefficient

The clustering coefficient developed by Watts and Strogatz measures the extent to which clusters or cliques exist in a network [WS98]. The clustering coefficent of each individual node is averaged to give the network level measure. A higher clustering coefficent shows that information diffusion happens locally and indicates a decentralized infrastructure [ORA].

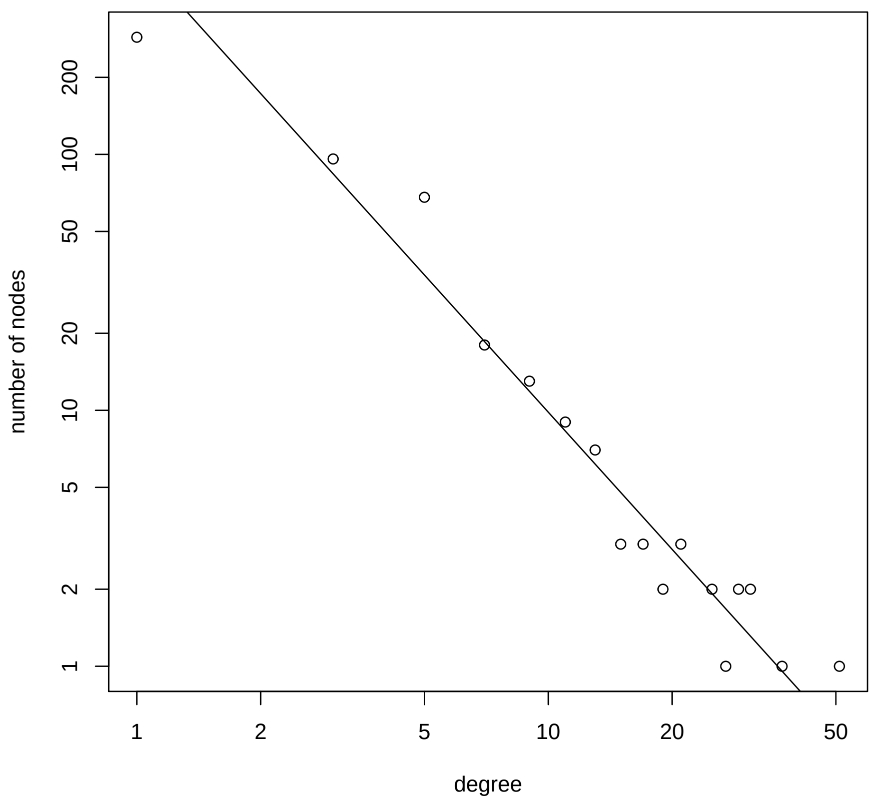


Figure 5: Log-log plot of the degree distribution for Tanzania's organization-to-organization network.

3.7 Network Centralization Measures

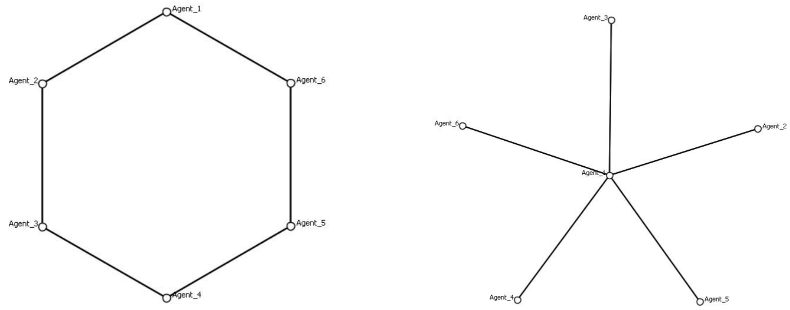
Centrality measures are node level measures, whereas centralization is a network level measure that describes the variability of node level centrality measures.

The general form of the equation for determining the centralization of a network is given by

$$C_X = \frac{\sum_{i=1}^{N}[C_X(p^*) - C_X(p_i)]}{max \sum_{i=1}^{N}[C_X(p^*) - C_X(p_i)]}, \tag{6}$$

the ratio of the sum of differences of centrality and the maximum theoretical sum possible for a network with N nodes. The derivation of this denominator for each specific centralization measure can be found in Freeman [Fre79].

The value of C_X is a standardized measure which ranges from 0 to 1. When $C_X = 0$, no node is more central than any other node. For example, in Figure 6a the circle graph for $N = 6$, no node is more central than any other node. The other extreme is the case when $C_X = 1$; here a single node is the most central as compared to the other nodes in the network as shown in Figure 6b by the star network for $N = 6$.



(a) (b)

Figure 6: (6a) Circle Network with $N = 6$ and (6b) Star Network with $N = 6$. (Figures created with ORA.)

Total Degree Centralization Degree Centralization gives a measure of how vulnerable a network is to fragmentation. The Degree centralization is given by the following equation:

$$C_D = \frac{\sum_{i=1}^{N} [C_D(p^*) - C_D(p_i)]}{(N-1)(N-2)}.$$

Here the maximum possible sum of differences in the denominator in (6) is given by $(N-1)(N-2)$ [Fre79].

A low degree centralization indicates a network where no single node is connected to all other nodes, therefore removal of any node still results in a highly connected network. For example, in the circle network shown in Figure 6a, the degree centralization, $C_D = 0$ since removal of any node leaves a network that remains entirely connected. A high degree centralization indicates there are a few nodes that are highly connected in the network. The removal of these highly connected nodes will likely result in a disconnected graph thereby making the network sensitive to fragmentation [MJ11]. The star network, shown in Figure 6b, has a degree centralization of 1 because removal of the central node leaves a completely disconnected network.

Betweenness Centralization Betweenness centrality measures the extent to which nodes lie between other nodes in a network. Betweenness centralization is a network level measure that indicates if a few nodes act as "gate-keepers" for the rest of the network. The betweenness centralization is defined as

$$C_B = \frac{\sum_{i=1}^{N} [C_B(p^*) - C_B(p_i)]}{(N-1)},$$

where the maximum possible sum of differences is $N - 1$.

Again, the value of the measure is standardized and ranges from 0 to 1. The case when $C_B = 0$ is the circle network shown in Figure 6a. Here no single node lies along the lines of communication between many other nodes. The star network, shown in Figure 6b, is an example where $C_B = 1$. In this case the central node lies between all other pairs of nodes on the periphery making it a "gate-keepers" for all communication in the network.

Closeness Centralization Closeness centrality is a node level measure that quantifies how close a node is to other nodes in the network by looking at geodesics from a given node to all other nodes. Closeness centralization is a network level measure that indicates on average how close nodes are to all other nodes in the network. The closeness centralization is defined as

$$C_C = \frac{\sum_{i=1}^{N}[C_C(p^*) - C_C(p_i)]}{(N-1)(N-2)/(2N-3)},$$

where the maximum possible sum of differences is $\frac{(N-1)(N-2)}{2N-3}$.

A closeness centralization of 1 indicates there is a single node that is directly connected to all other nodes. For example the star network in Figure 6b has a central node directly connected to all other nodes. A closeness centralization of 0 indicates that any given node has the same connection pattern as any other node in the network. If one were to list the geodesics from a particular node to all other nodes, this list would be identical regardless of the node chosen.

3.8 Clique Membership Count

A clique in a network is a subgraph or subset of the network that consists of 3 or more nodes where the nodes are connected to every other node in the subset. The clique membership count gives the number of distinct cliques that a node belongs to. Finding cliques in a network gives cohesive subgroups of the network; however, the mathematical definition is strict, requiring a link between each pair of nodes in the network ([WF94], [ORA]).

3.9 Simmelian Ties

Simmelian ties are closely related to cliques. Any two members of a clique have Simmelian ties, or ties that are reciprocal and strong. As Krackhardt [Kra98] describes, this strong tie is reinforced in the pair by each person having a common tie to a third person. Krackhardt bases the quantitative examination of these ties on the work of sociologist Simmel, who stresses the importance of triads in an organization's structure. Simmel argues that triads preserve more individuality. Members of a triad have less bargaining power, and conflict can be more easily resolved in a triad [Kra98].

4 Agent to Agent Networks

In general, the agent networks of Ghana and Tanzania are quantitatively similar; however, Trinidad and Tobago's network is markedly different. This seems logical based on each country's post-independence history as well as geographic differences. Both Ghana and Tanzania continue to evolve from their African-socialist roots after independence from Great Britain in the 1960s. Both nations also implemented International Monetary Fund (IMF) structural adjustments in 1992 in which they liberalized their economies and accepted multipartyism. Trinidad and Tobago, which gained its independence around the same time, adopted a British capitalist model. Trinidad's closeness to rich markets in North and South America and its economic links throughout the West Indies helped forge its economic path. Additionally, because Trinidad and Tobago is an island nation with close ties to its neighbors, it is more dependent on cross-border trade. Conversely, both Ghana and Tanzania

originally established insular, self-supporting, centrally planned economies. We hypothesize that the different influences of each country's history, economic development models, and geographic location have resulted in networks that exhibit different characteristics.

4.1 Agent to Agent Node-Level Centrality Metrics

Table 2 contains some average node-level centrality measures for the three markets studied.

Table 2: Average Node-Level Centrality Measures for Agent by Agent Networks. For closeness centrality, the largest connected component of the network was used.

Measure	Tanzania	Ghana	Trinidad and Tobago
Total Degree Centrality	0.021	0.025	0.029
Eigenvector Centrality	0.041	0.044	0.067
Closeness Centrality	0.388	0.392	0.435
Betweenness Centrality	0.004	0.005	0.008
Clique Membership Count	3.141	2.720	4.229
Simmelian Ties	0.060	0.070	0.104
Clustering Coefficient	0.804	0.822	0.723

A node-level agent network comparison confirms that Trinidad's network is much different than the two African networks. The average total degree, eigenvector, and closeness centrality measures for all countries are fairly low, but Trinidad's values are measurably higher. Average betweenness centrality was also low in all three networks but Trinidad's values were 1.5 times greater than Tanzania's and 2 times greater than Ghana's. This measure suggests that the Trinidad network has a greater number of agents that can be considered power brokers that bridge the gap between connected and unconnected agents. Trinidad also had a slightly higher clique membership count and more simmelian ties. This implies that agents in Trinidad are affiliated with more distinct groups and may have stronger ties to the groups with which they are linked.

4.2 Individual Agent Centrality Metrics

The prior discussion was based on average measures of centrality, which may fail to identify important distinctions among the countries of interest. Therefore, we also analyzed which agents in each country were most prominent based on each centrality measure. We maintained anonymity of these agents by identifying them by their Agent Identification Number from our database.

The results of this analysis are depicted in Table 3. Figures 7 to 9, Figures 10 to 12, Figures 13 to 15, and Figures 16 to 18 show the distributions for degree, closeness, betweenness, and eigenvector centrality, respectively. Ghana has one agent (165) who exhibits a much higher degree centrality value than prominent agents in all three networks. Agent 165 has a degree centrality measure of 0.118 while all prominent agents in the other networks have values between 0.075 and 0.094.

When looking at closeness centrality, the prominent agents have similar values ranging from 0.588 to 0.528 across all network (examining the largest connected components of each network). When comparing the distribution of values, we see that Ghana and Trinidad and

Table 3: Top agents in various centrality measures

	Tanzania		**Ghana**		**Trinidad & Tobago**	
Metric	Agent	Value	Agent	Value	Agent	Value
Total Degree Centrality	125	0.083	165	0.118	121	0.09
	203	0.081	128	0.094	45	0.088
	162	0.075	172	0.094	91	0.08
Closeness Centrality (largest connected component)	125	0.565	165	0.563	45	0.588
	203	0.546	128	0.546	91	0.586
	153	0.541	178	0.535	121	0.584
			237	0.526	64	0.580
			11	0.528		
Betweenness Centrality	162	0.094	237	0.13	138	0.072
	207	0.055	165	0.087	112	0.063
	125	0.055	128	0.072	45	0.062
Eigenvector Centrality	125	0.293	165	0.244	121	0.278
	203	0.286	177	0.233	64	0.273
	162	0.247	172	0.232	91	0.265
			178	0.231	45	0.262
			128	0.23		
Clique Membership Count	107	30	165	23	45	27
	203	23	158	19	121	24
	125	23	172	15	91	23
	29	20	106	15	64	23
Simmelian Ties	203	0.234	165	0.326	45	0.32
	125	0.228	237	0.26	91	0.292
	162	0.215	128	0.25	121	0.287

Tobago have larger proportions of agents in this high range, given by Figures 11 and 12 as compared to Tanzania which has few agents with closeness centrality values above 0.53 as shown in Figure 10.

As we saw with degree centrality, one agent in the Ghana network exhibits a much higher betweenness centrality than all other prominent agents. As shown in Figure 14, Agent 237's value of 0.13 is significantly higher than all other prominent agents. The Tanzanian network also has an agent (162) who exhibits a significantly higher betweenness centrality value (0.094 vs. 0.055) than the other prominent agents in its network also shown in Figure 13.

When measured based on eigenvector centrality, all three networks exhibit similar prominent agent characteristics with values ranging from 0.18 to 0.29 as shown in Figures 16, 17 and 18. In general, the agents in the Ghana network have lower eigenvector centrality values than the prominent agents in the other two networks.

Clique membership count provides a comparison of the effective size of an agent's social network based on redundancy of ties. One agent in the Tanzanian network (107) and one in the Trinidad network (45) have significantly higher values than all other prominent agents (30 and 27). Generally, the Ghana network's prominent agents have relatively lower clique count values. Simmelian ties measures how often an agent is reciprocally and strongly tied to another agent and these two agents have the same strong relationship with a common third node. Ghana and Trinidad's most prominent agents have stronger simmelian ties than Tanzania's agents.

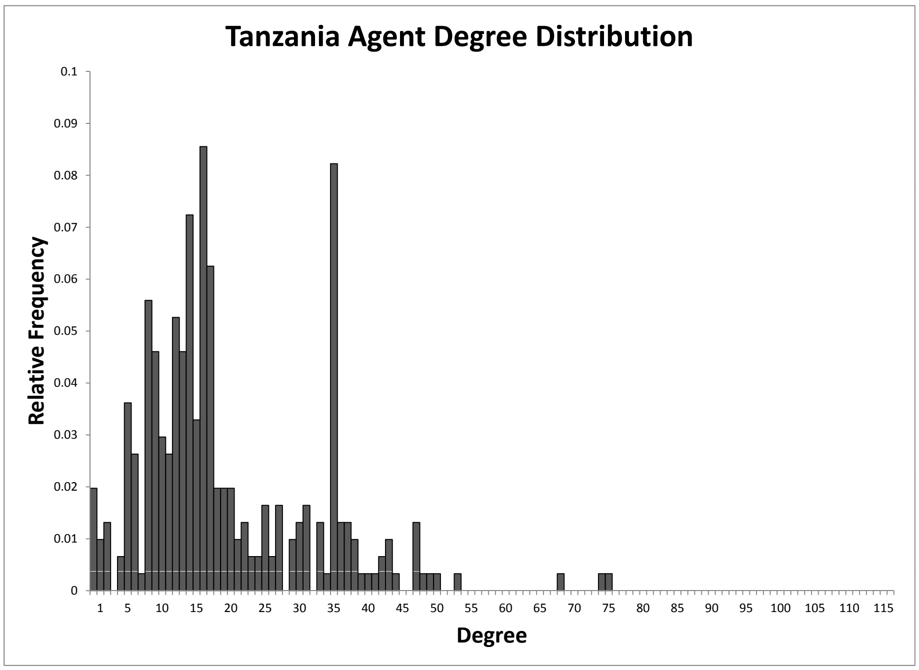


Figure 7: Degree distribution for Tanzania's agent-to-agent network.

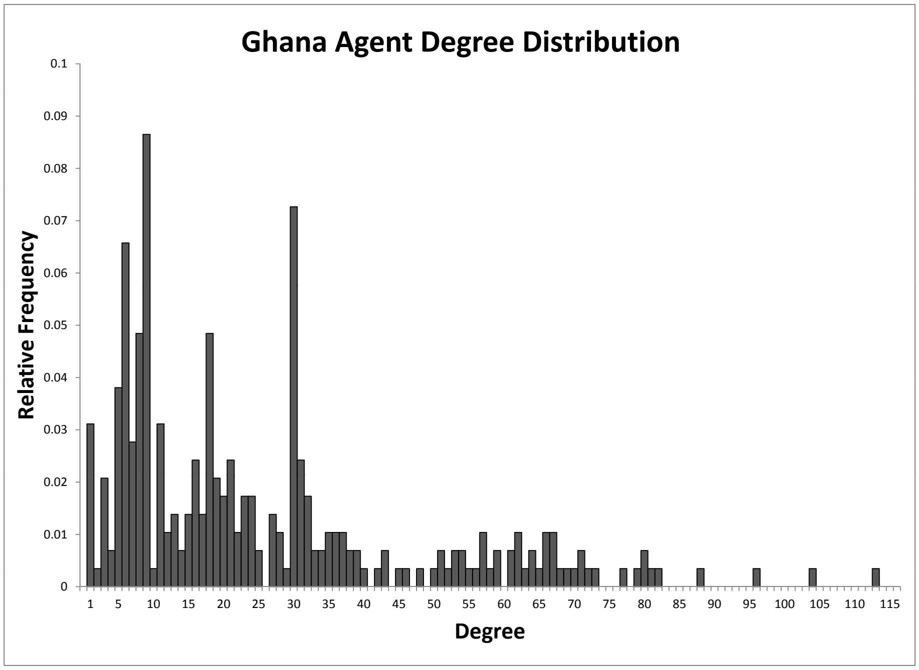


Figure 8: Degree distribution for Ghana's agent-to-agent network. Note the agent (identified as Agent 165) with the highest degree compared to agent-to-agent networks for all three countries.

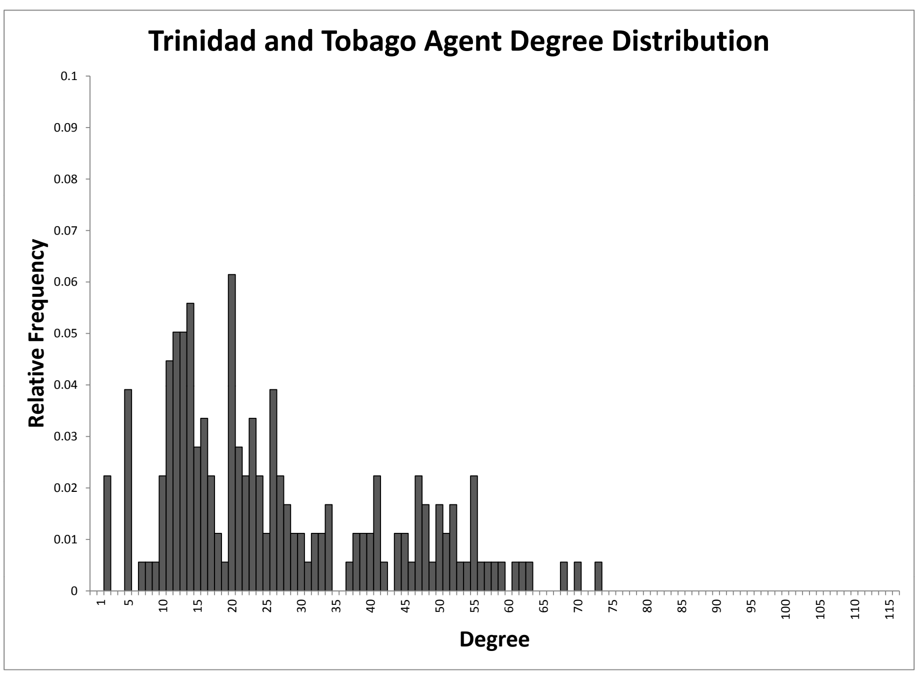


Figure 9: Degree distribution for Trinidad and Tobago's agent-to-agent network.

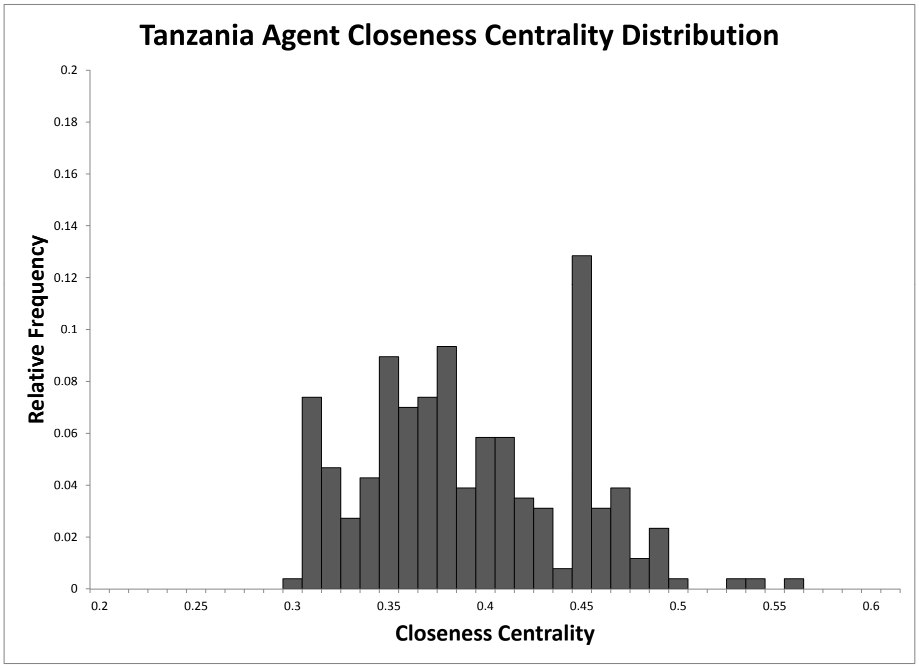


Figure 10: Distribution of closeness centrality values for Tanzania's agent-to-agent network.

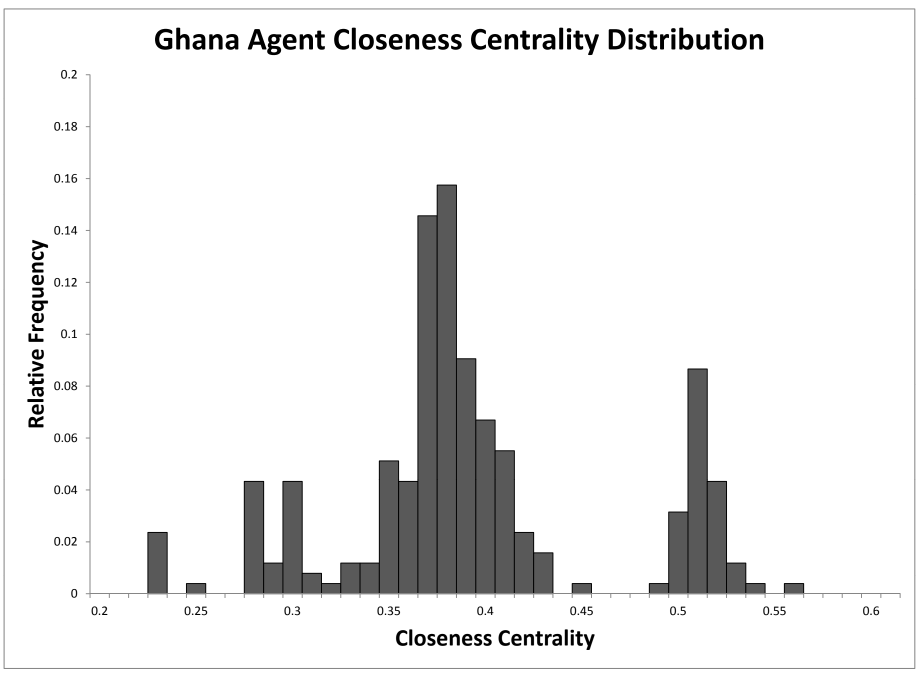


Figure 11: Distribution of closeness centrality values for Ghana's agent-to-agent network.

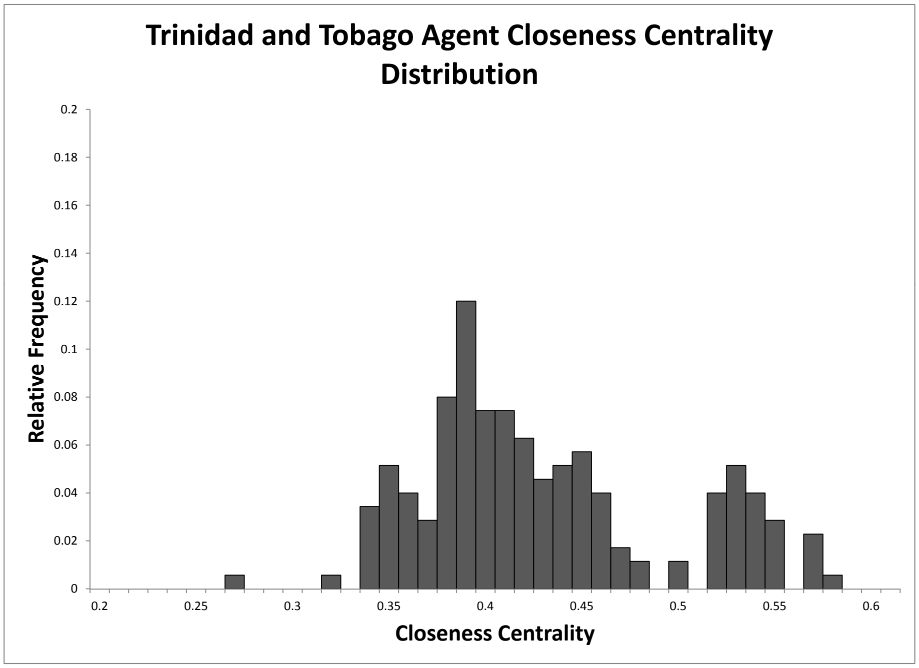


Figure 12: Distribution of closeness centrality values for Trinidad and Tobago's agent-to-agent network.

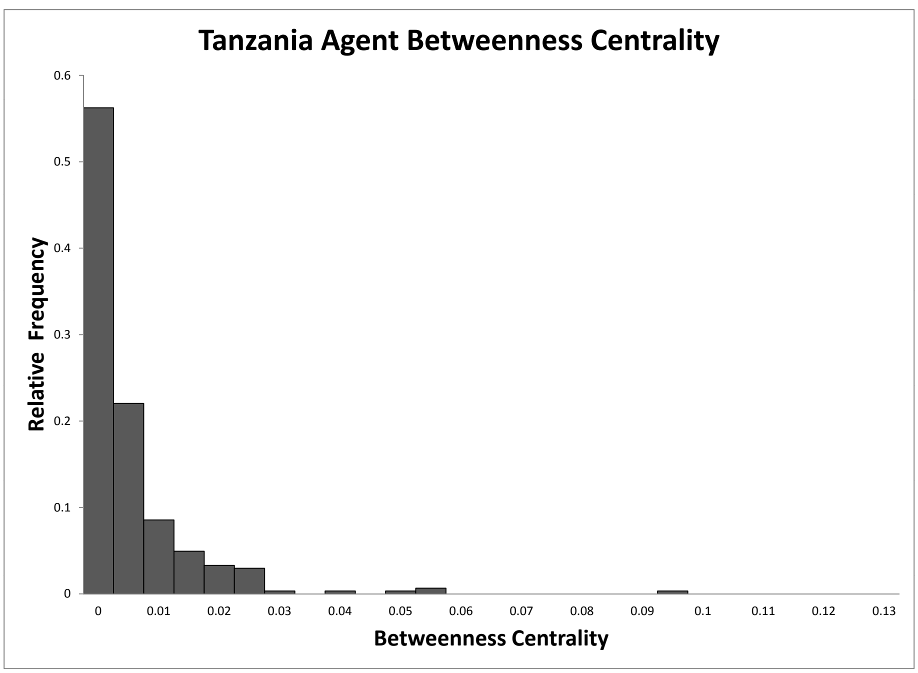


Figure 13: Distribution of betweenness centrality values for Tanzania's agent-to-agent network.

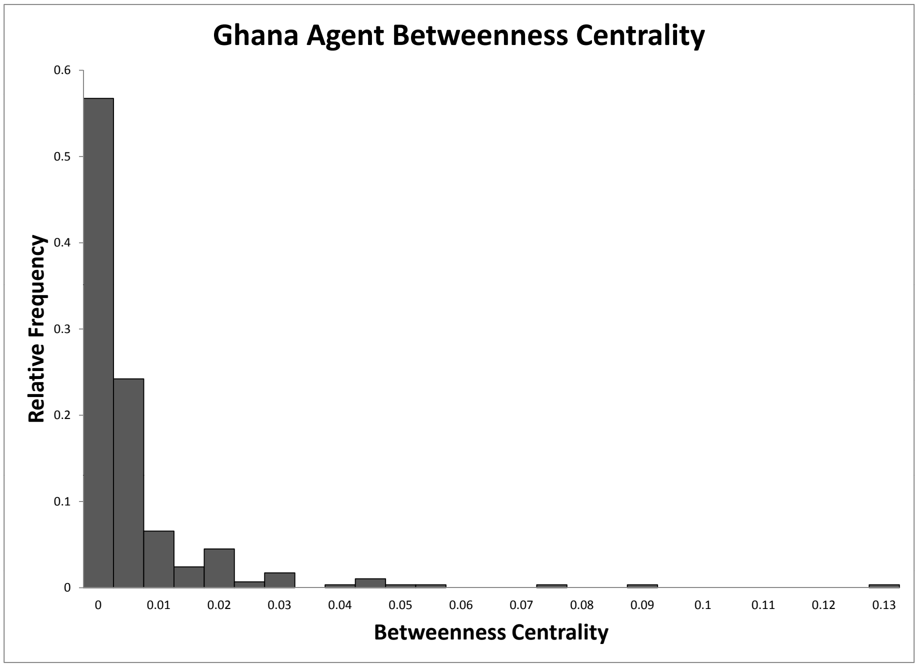


Figure 14: Distribution of betweenness centrality values for Ghana's agent-to-agent network. Note the agent (identified as Agent 237) with the highest betweenness centrality value (0.13) of all agent-to-agent networks.

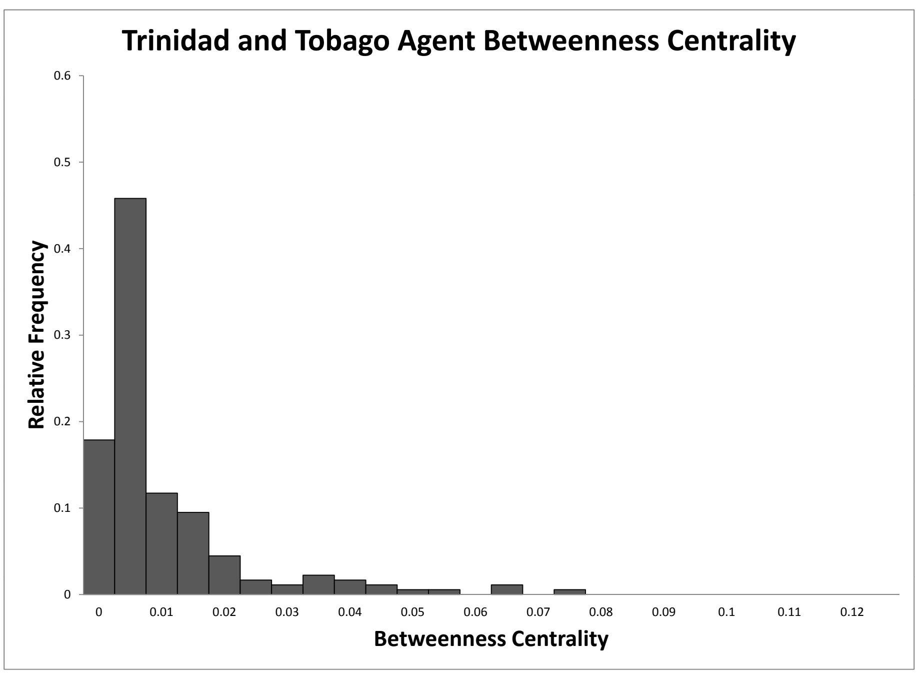


Figure 15: Distribution of betweenness centrality values for Trinidad and Tobago's agent-to-agent network.

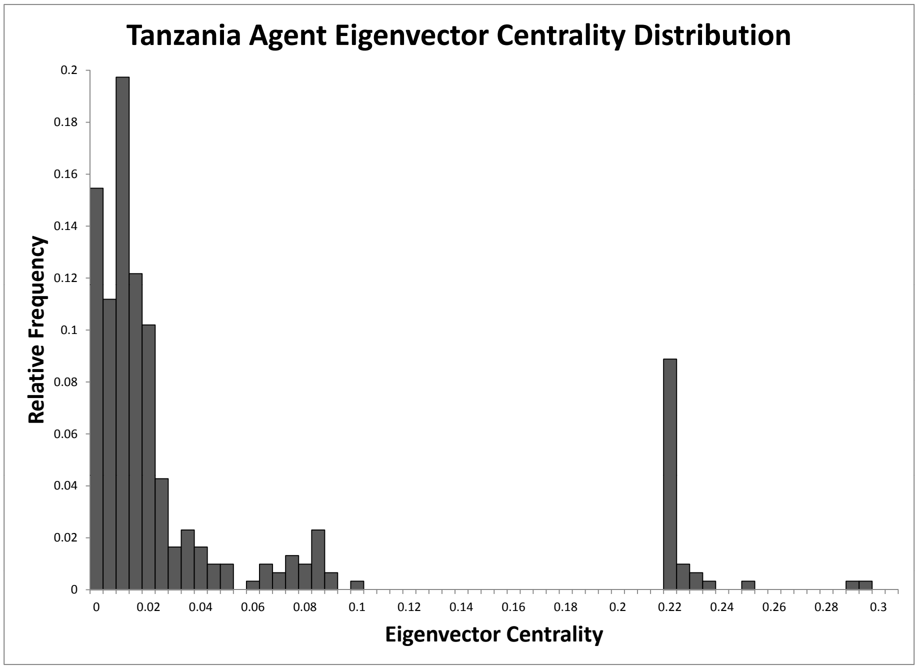


Figure 16: Distribution of eigenvector centrality values for Tanzania's agent-to-agent network.

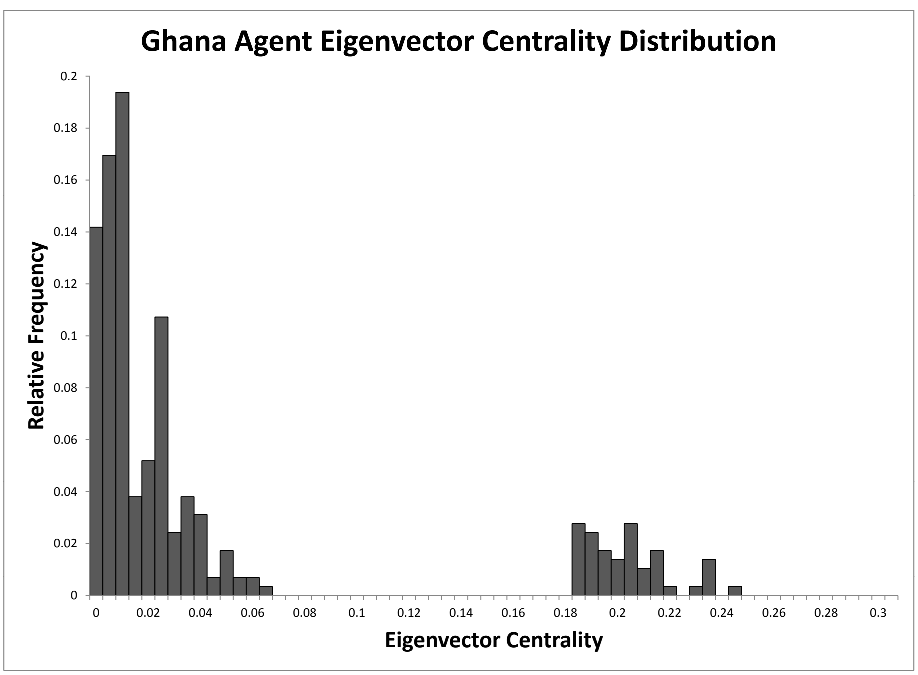


Figure 17: Distribution of eigenvector centrality values for Ghana's agent-to-agent network.

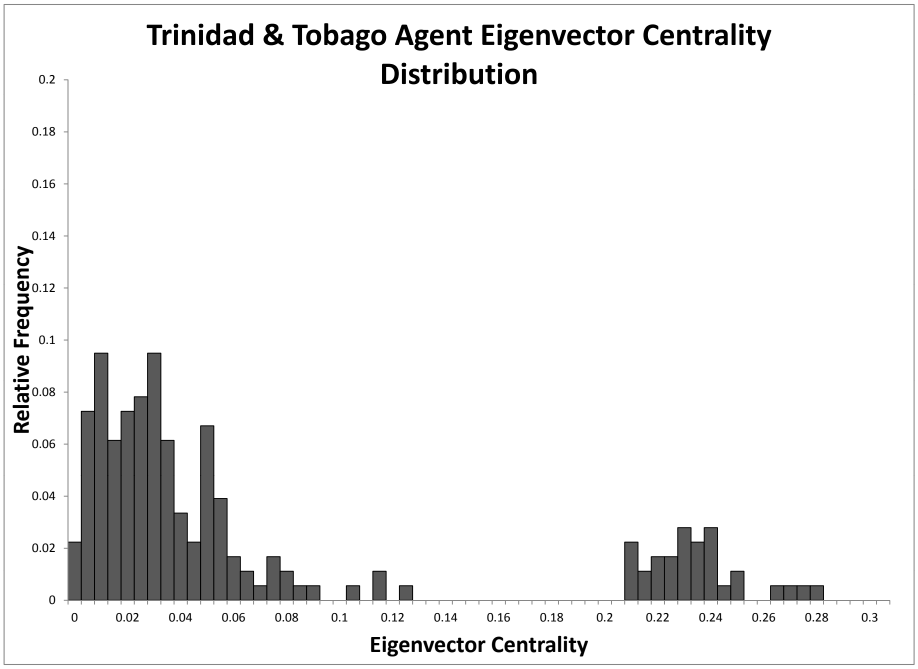


Figure 18: Distribution of eigenvector centrality values for Trinidad and Tobago's agent-to-agent network.

4.3 Prominent Agents by Country

Tanzania Tanzania's network has a greater diversity of prominent agents than Ghana's. Agent 125 figures prominently in the Tanzania agent network. He is the "top node" in both degree centrality and eigenvector centrality. Additionally, he is among the most prominent agents in the other descriptive metrics categories. He is currently a member of a major Tanzanian industry association and a law firm. He also serves on the board of an insurance company and was previously employed by, or a member of the following organizations: the United Nations, an international consulting firm, a parastatal investment bank, a nationalized manufacturing firm, and two law societies. A graduate of University of Dar es Salaam, he has taught at both the University of Dar es Salaam and the Institute of Financial Management in Dar es Salaam.

Agent 203 had the strongest simmelian ties and was the second highest agent in clique count, degree centrality, and eigenvector centrality. He graduated from the University of Dar es Salaam and is currently affiliated with a parastatal venture capital firm and a commercial bank. He is a member of a major Tanzanian industry association and a director of two financial markets development associations and a secondary school. He has previously worked with four international banks with subsidiaries in Tanzania.

Agent 162 was highest in betweenness centrality value and a prominent agent in degree centrality and eigenvector centrality with strong simmelian ties. He is currently affiliated with a major gas company, a private sector foundation, and a major Tanzanian industry association. He serves on numerous boards including a brewery, a South African bank's Tanzanian subsidiary, the national energy company, and a regional business development

council. He was previously associated with a parastatal investment venture capital fund, a nationalized beverage firm, and a parastatal economic development firm, and an airport development council. Furthermore, he formerly held two key positions in the Tanzanian government.

Ghana The Ghana network has a concentrated group of agents who rank high in prominence in the agent network descriptive metrics. Agent 165 figures prominently in the Ghana agent network. He is the "top node" in all agent network descriptive measure except for betweenness, where he ranks second. Agent 165 is prominent leader in the Ghana Stock Exchange and a graduate of the University of Ghana. He is currently an owner or employee of the following businesses: three Pan-African banks and one Ghana-based holding company, a major development financing institution, an asset management firm, and two US-based financial institutions.

Agent 128 is a top node in all categories except for clique count. He is a member of the Regional House of Chiefs and one of Ghana's State Councils. A graduate of the University of Ghana, he is currently an owner or employee of a commercial bank, two finance groups, two brokerages, and a consulting firm. He is also on the board of an aluminum processing company, an aluminum factory, a communications and technology firm, a power company, a kitchenware manufacturer, a major sporting club, and the National Theater of Ghana. He was previously employed at a parastatal bank, a nationalized agricultural product marketing board, and a financial firm.

Agent 172, a top node in three of the metric categories, is currently an owner, employee, or member of a Pan-African bank and the Institute of Chartered Bankers. He is on the board of a Nigerian bank and was previously employed at a parastatal bank and another Pan-African bank.

Agent 237 has very high closeness and betweenness values as well as strong simmelian ties indicating he may serve a critical bridging function in the network. He is currently an employee or member of a major industry association, a major international consulting, and a leading Ghanaian software developer. He is also a graduate of University of Ghana.

Trinidad and Tobago Interestingly, agent 138 has a high betweenness centrality, but is not prominent in any other network metric. One agent (45) is very prominent in the metrics that exhibit bridge characteristics, while another agent (121) is prominent in two of the traditional centrality metrics – degree and eigenvector.

Agent 121 is the top node in both centrality and eigenvector centrality agent network descriptive measures. Additionally, he is among the most prominent agents in the other descriptive metrics categories except for betweenness centrality. He is currently employed by a financial services firm and a member of two professional associations. He has served on the board of a Jamaican life insurance company and a Jamaican urban development organization. He is a graduate of the University of the West Indies.

Agent 45 graduated from the University of the West Indies and is a prominent agent in all three centrality metrics, and the most prominent in clique count and simmelian values. He is currently affiliated with the Trinidad and Tobago Stock Exchange, a brokerage firm, and a federal anti-corruption commission. He is also on the board of a Barbadian cement company, an export business, a flour manufacturer, and a venture capital fund.

Agent 138 is a prominent agent only in terms of betweenness. He is affiliated with a

brokerage firm, a financial services company, and a United Nations Commission. He is a director of a Jamaican life insurance company and the Jamaican subsidiary of a Canadian bank, who previously served as a member of the Attorney General's Chambers and two legal committees. He graduated from the University of the West Indies.

4.4 Agent to Agent Network Centralization Metrics

Table 4 contains comparative network-level metrics for the three markets studied. Ghana and Tanzania have very similar node counts while Trinidad and Tobago has considerably fewer. The Trinidad network has almost 40% fewer nodes (179 vs. approximately 300). The Trinidad network also contains approximately 40% fewer links. These differences could be attributed to several factors from the cultural and historic differences discussed above to inconsistency in data collection by the different research teams.

Table 4: Agent Network-Level Measures

Measure	Tanzania	Ghana	Trinidad and Tobago
Node Count	304	289	179
Link Count	2773	2939	1679
Node Count (largest connected component)	257	254	175
Link Count (largest connected component)	2564	2872	1677
Density	0.0602	0.0706	0.1054
Diffusion	0.7150	0.7692	0.9486
Diameter	304	289	179
Average Distance	2.6255	2.6754	2.4074
Fragmentation	0.2812	0.2263	0.0442
Clustering Coefficient Watts-Strogatz	0.8039	0.8222	0.7227
Total Degree Centralization	0.0618	0.0940	0.0612
Betweenness Centralization	0.0909	0.1256	0.0646
Closeness Centralization (largest connected component)	0.339	0.337	0.310
Eigenvector Centralization	0.2537	0.2015	0.2130

The density of the Trinidad and Tobago network (0.105) is considerably higher, as compared to Ghana (0.070) and Tanzania (0.060). Lower density indicates that power is shared more equally among agents so this metric suggests that the Trinidad network might contain more key agents who wield power or influence. This greater density leads to a higher diffusion metric for the Trinidad and Tobago network. Diffusion computes the degree to which information could be easily spread throughout the network. A large diffusion value means that nodes are close to each other; a smaller value indicates nodes are farther apart. Trinidad and Tobago's network also exhibits a slightly smaller average distance metric (2.4 vs. approximately 2.6), which is logical because average distance describes, how far any two nodes are apart in the network.

Another difference between Trinidad and the other two networks is a significantly lower clustering coefficient (0.72 vs. approximately 0.81). This metric demonstrates that the Trinidad network is has a smaller number of sub-groups than the other two networks. So,

the Trinidad agent network is more dense but less clustered than the agent networks of Ghana and Tanzania. The Trinidad network also has a much lower proportion of nodes in a network that are disconnected based on the fragmentation metric (0.044 vs 0.226 and 0.281).

Total degree centralization is fairly low for each agent network (less than 0.10). This measure informs us that no particular nodes, or agents, are highly central in the network. As an example, a star network topology would have a high total degree centralization value (1.0). Interestingly, Ghana's metric is significantly larger than that of the Tanzania and Trinidad networks (0.09 vs. 0.06). This statistic indicates there are potentially several agents in the Ghana agent network that are more central to the network than in the other two networks contradicting insights gained by analyzing the density metric.

Betweenness centralization is significantly greater in the Ghana network than in Tanzania and Trinidad (0.125 vs. 0.091 and 0.065). Networks with higher betweenness centralization have more intermediaries, or bridges, connecting disconnected groups. The Tanzania network has an eigenvector centralization value that is significantly larger than Ghana and Trinidad (0.254 vs. 0.201 and 0.213), which suggests that Tanzania has more leaders of strong cliques who are connected to others that are themselves highly connected.

The closeness centralization measure for the largest connected component in each agent network is similar with Trinidad and Tobago's slightly lower. This shows that the extent to which information flows are centralized around single agents or groups is comparable across all three market networks.

5 Organization to Organization Networks

5.1 Organization to Organization Node-Level Centrality Metrics

Table 5 contains comparative node-level metrics for the three markets studied. A node-

Table 5: Average Node-Level Centrality Measures for Organization by Organization Networks. For closeness centrality, the largest connected components of the network was used.

Measure	Tanzania	Ghana	Trinidad and Tobago
Total Degree Centrality	0.001	0.002	0.002
Eigenvector Centrality	0.021	0.023	0.029
Closeness Centrality	0.247	0.258	0.274
Betweenness Centrality	0.002	0.002	0.003
Clique Membership Count	1.044	1.055	1.126
Simmelian Ties	0.006	0.005	0.007
Clustering Coefficient	0.528	0.661	0.636

level organization network comparison also reveals that Trinidad's network is only slightly different than the African networks. Although average degree centrality was quite low in all three networks, both Trinidad's and Ghana's average degree centrality were two times Tanzania's. This measure suggests that Tanzania's organizations are less connected to each other than organizations in the other countries. Average closeness centrality measures in the largest connected component were similar, but slightly higher in Trinidad and Tobago. The

average eigenvector centrality measures are also comparable, with Trinidad and Tobago's measure slightly higher, so Trinidad's most important organizations may be more connected to other highly connected organizations. While measures of betweenness centrality were low across the board, Trinidad's measure was higher than the African countries' metrics. Nodes high in betweenness centrality are often considered power brokers that bridge the gap between connected and unconnected nodes. Trinidad also had a slightly higher clique membership count and more simmelian ties. Thus, organizations in Trinidad are affiliated with more distinct groups and may have stronger ties to the organizations with which they are linked.

5.2 Individual Organization Centrality Metrics

As mentioned previously, this analysis was based on average measures of centrality, which may fail to identify important distinctions among the countries of interest. Thus, researchers analyzed which organizations in each country were most prominent based on each centrality measure. The results of this analysis are depicted in Table 7 in Appendix A (Section 8) and are illustrated in the distributions given in Figures 19 to 30.

Ghana's most prominent organizations have higher degree centrality than prominent organizations in the other networks so they may exert more direct influence on the network than their counterparts. This is also seen in Figure 20, where the Ghana organization network degree distribution shows a single node with degree 78 whereas the highest degree for Tanzania is 51(Figure 19) and Trinidad and Tobago is 42 (Figure 21). Specifically, Ghana's Ecobank exhibited degree centrality that was twice that of the most prominent organizations in the other networks. The organizations with the most links in Ghana were two banks (Ecobank and CAL Bank Limited) and the University of Ghana. In Trinidad, a conglomerate (ANSA McAL Limited) and the University of the West Indies were most connected, while in Tanzania the organizations with the most links were a professional association (the CEO Roundtable) and the Ministry of Finance and Economic Affairs. As with the agent networks, the organization networks are characterized by similar closeness centrality distributions.

Organizations high in betweenness centrality lie on paths between other organizations and thus may influence these organizations by controlling information flows. Based on this metric, Trinidad's key organization was the Institute of Chartered Accountants (with a value of 0.188), 63% higher than Tanzania's CEO Roundtable (0.115) and 18% higher than Ghana's Ecobank (0.159). The distribution of the betweenness centrality values for each country's organization network is shown in Figures 25, 26 and 27. Note that in each of the networks over 70% of the organizations have 0 or near 0 betweenness centrality values indicating there are few organizations controlling information flow. Interestingly the organizations that could be considered information brokers in Ghana and Trinidad were both professional organizations, while once again in Ghana, Ecobank played a key role.

Ghana's Ecobank was also an outlier in terms of eigenvector centrality suggesting that Ecobank may have more influence in Ghana due to its connections to other influential organizations. Ecobank's eigenvector centrality at 0.716 was more than 1.5 times Tanzania's Ministry of Finance and Trinidad's Institute of Chartered Accountants. The eigenvector centralities of the other most prominent organizations in each network were largely similar as shown in the distributions in Figures 28, 29 and 30.

A clique is a group of three or more nodes (or organizations) that are directly connected

to all the other nodes (organizations) in the group. Tallying the number of distinct cliques to which each organization belongs produces its clique membership count. The two most prominent organizations in Ghana were members of more cliques than their counterparts in the other networks. Ecobank was associated with 21 cliques and CAL Bank was a member of 17. In Tanzania, the CEO Roundtable was affiliated with 16 cliques, followed by the Ministry of Finance with 14 affiliations. The organizations in Trinidad that were members of the most cliques were ANSA McAL and the University of the West Indies each with 14. Ghana's Ecobank also had the strongest simmelian ties (measuring 0.102), which was 52% higher than the most prominent organization in Trinidad (ANSA) and 76% higher than the Ministry of Finance in Tanzania.

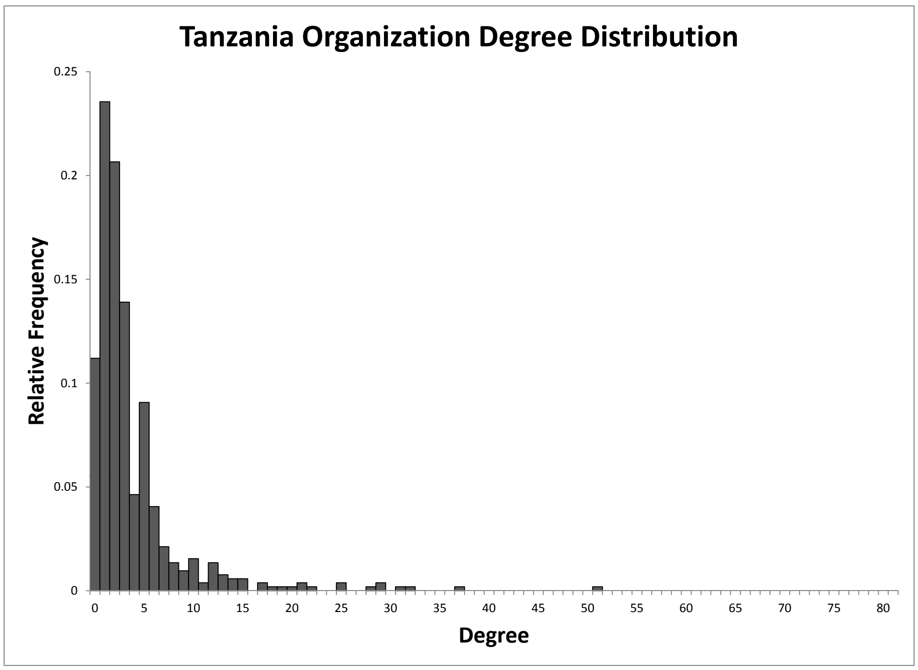


Figure 19: Degree distribution for Tanzania's organization-to-organization network.

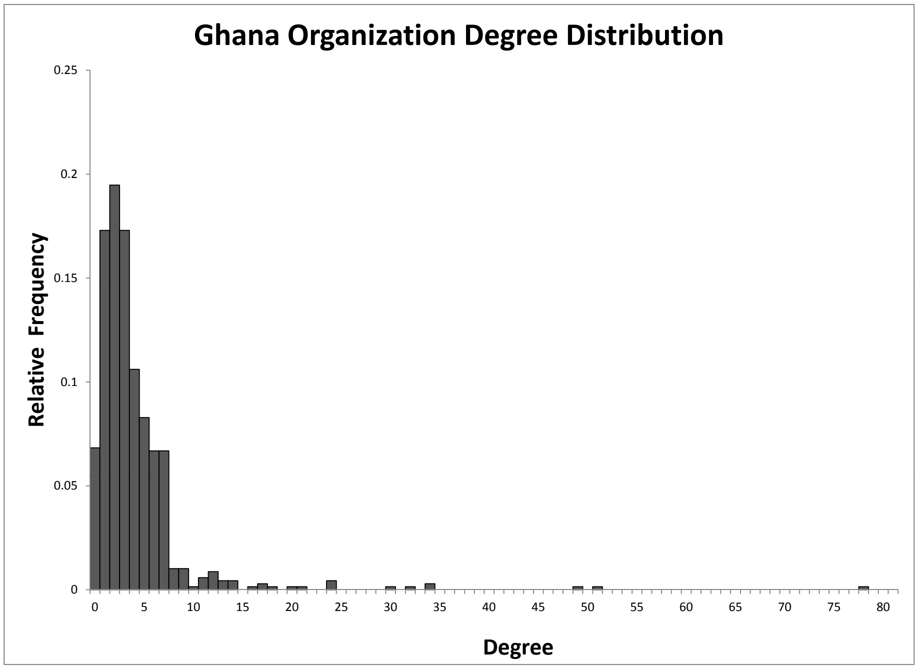


Figure 20: Degree distribution for Ghana's organization-to-organization network. Note the agent with degree 78 has the highest degree for any of the organization-to-organization networks.

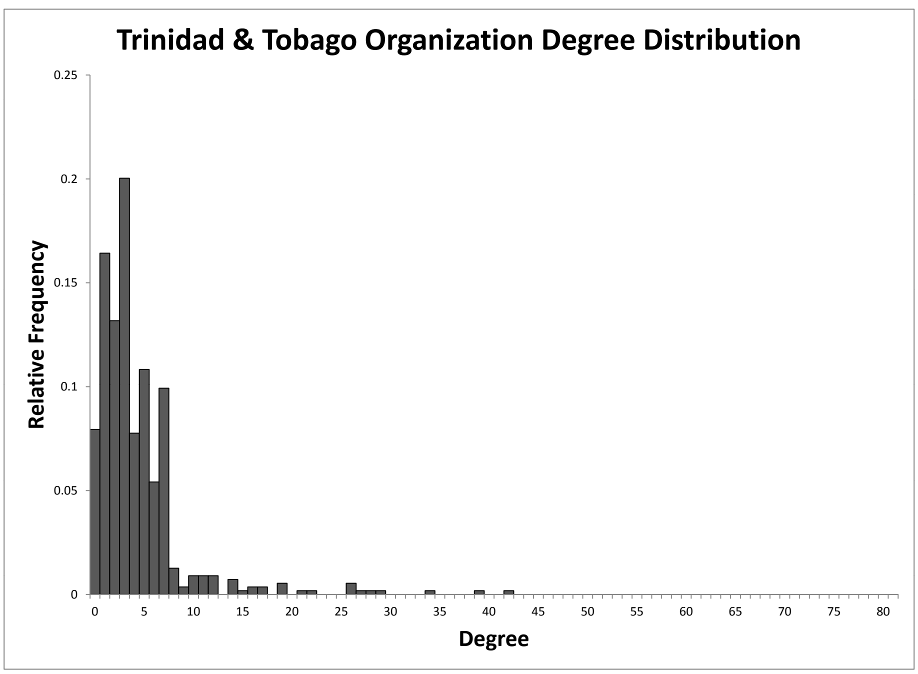


Figure 21: Degree distribution for Trinidad and Tobago's organization-to-organization network.

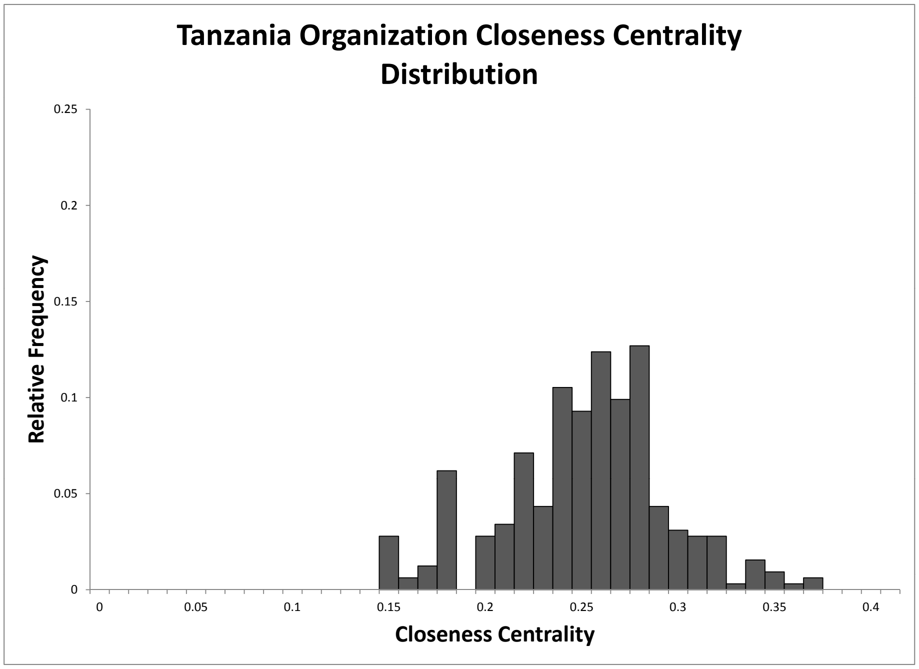


Figure 22: Distribution of closeness centrality values for Tanzania's organization-to-organization network.

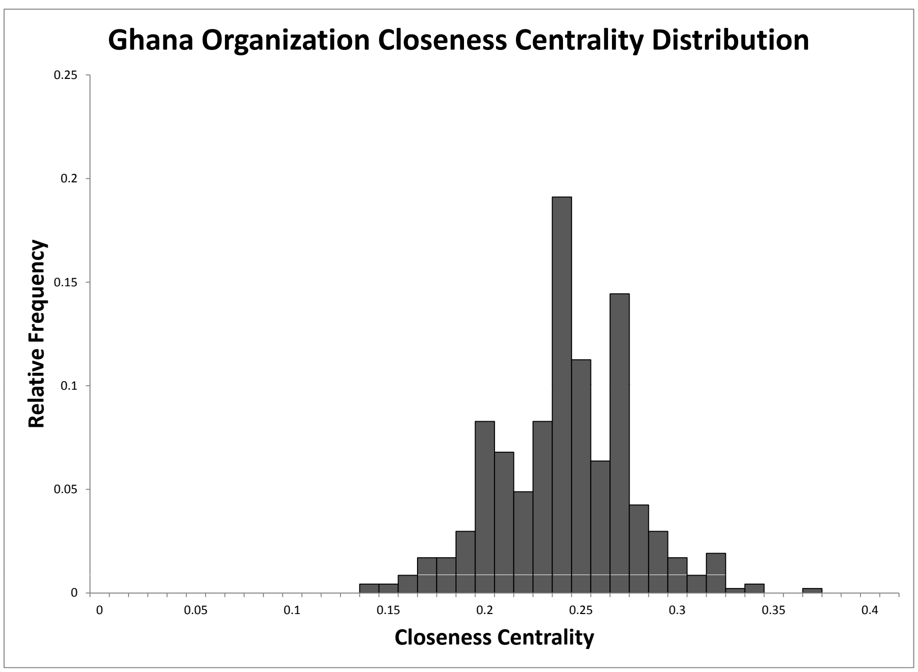


Figure 23: Distribution of closeness centrality values for Ghana's organization-to-organization network.

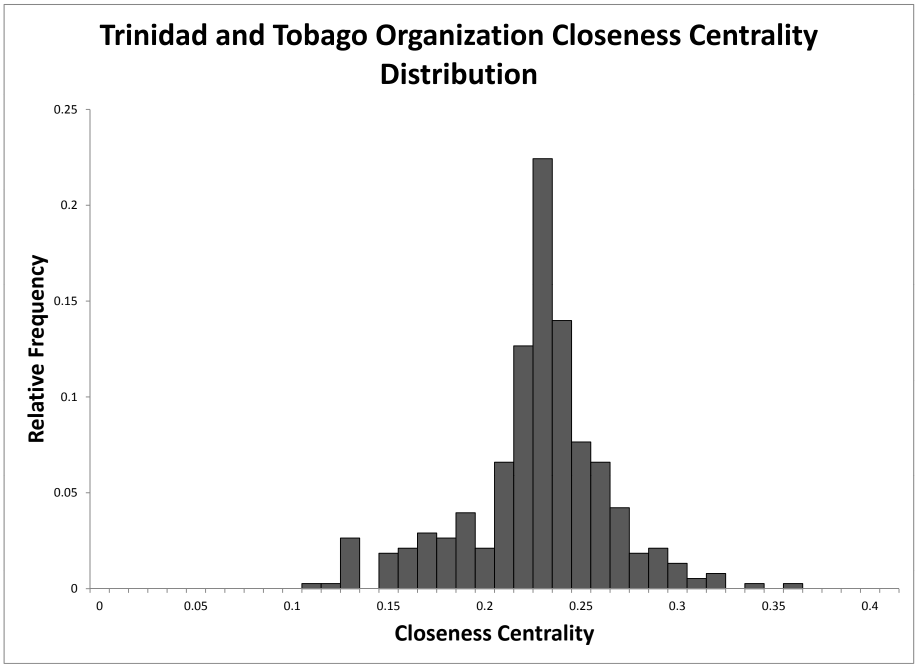


Figure 24: Distribution of closeness centrality values for Trinidad and Tobago's organization-to-organization network.

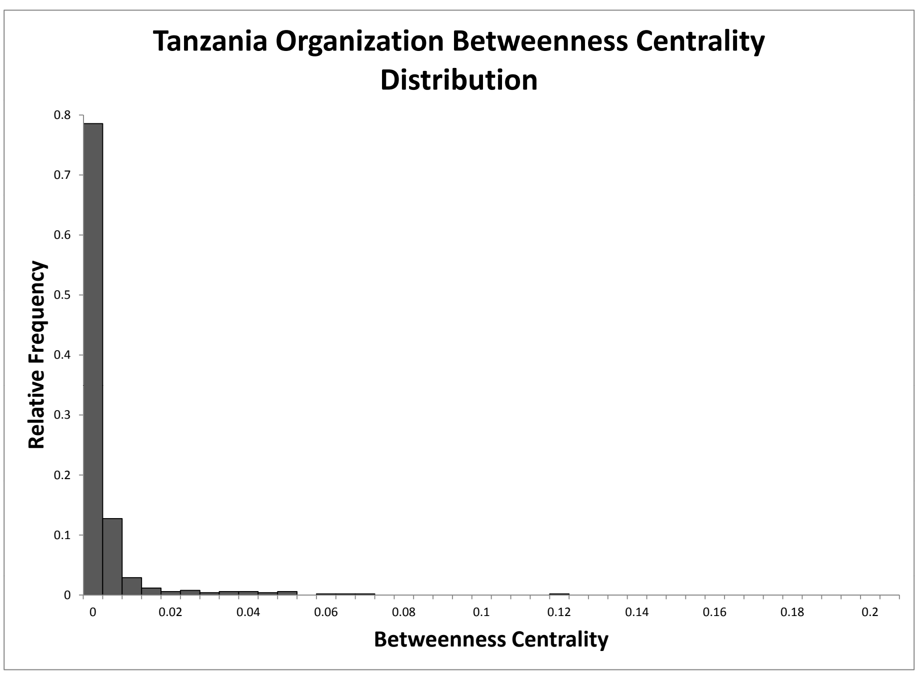


Figure 25: Distribution of betweenness centrality values for Tanzania's organization-to-organization network.

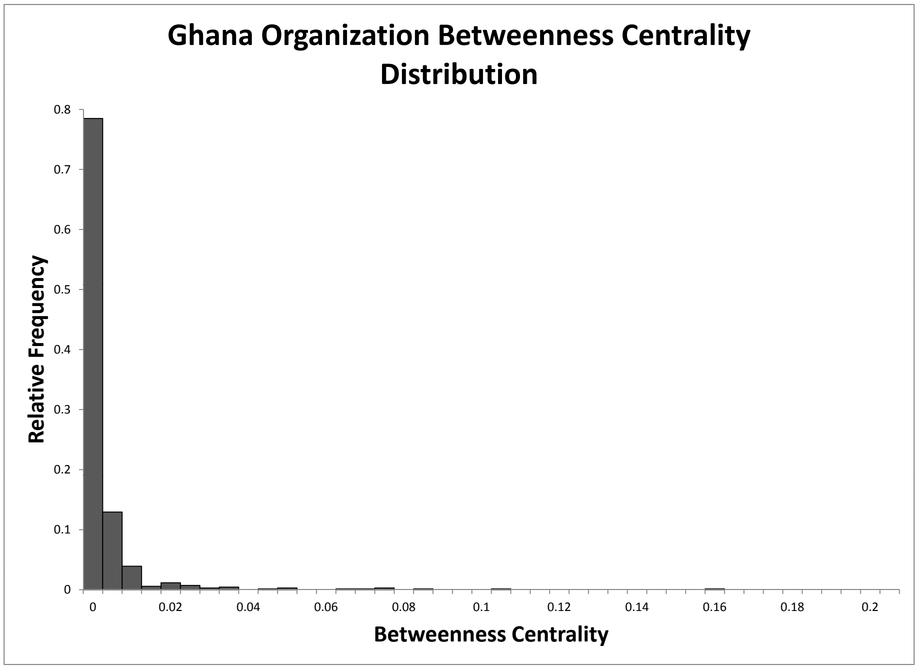


Figure 26: Distribution of betweenness centrality values for Ghana's organization-to-organization network.

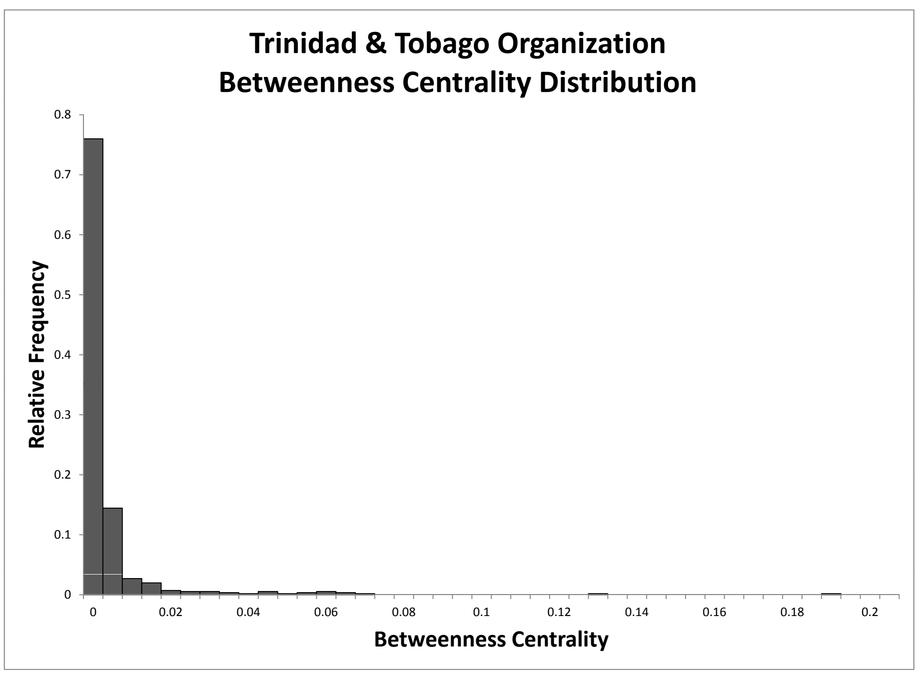


Figure 27: Distribution of betweenness centrality values for Trinidad and Tobago's organization-to-organization network.

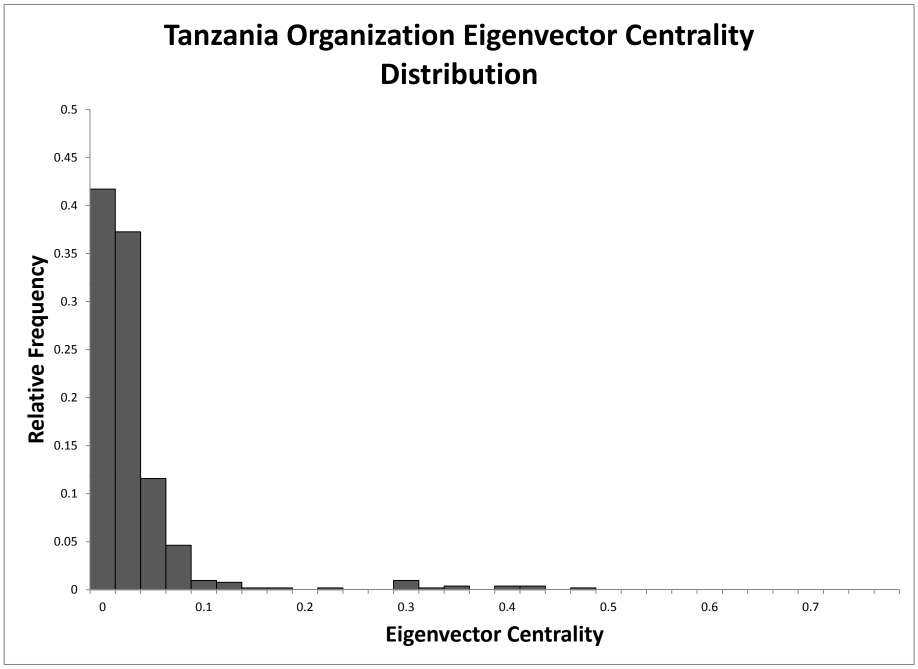


Figure 28: Distribution of eigenvector centrality values for Tanzania's organization-to-organization network.

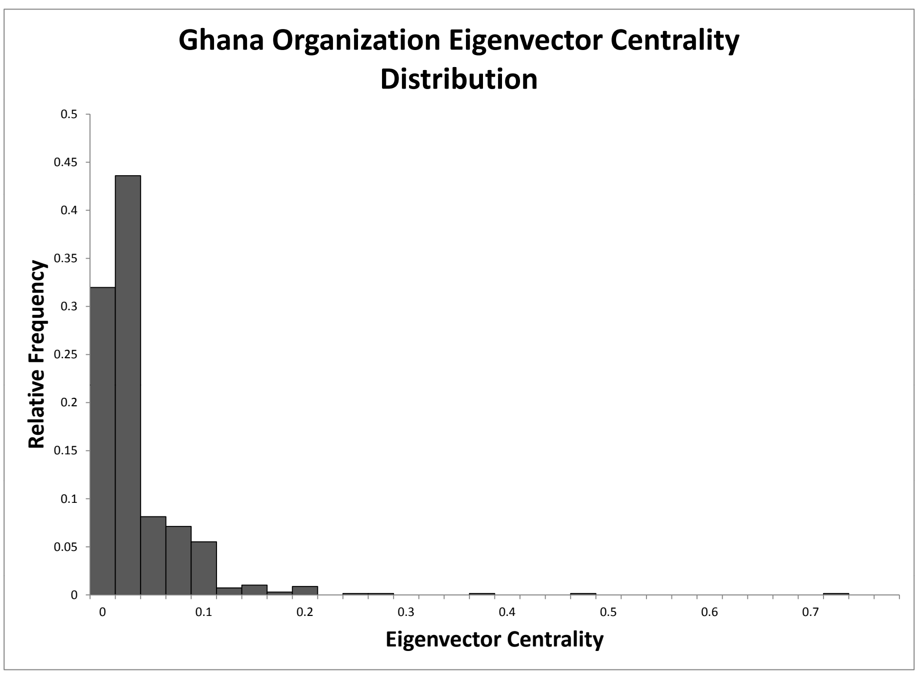


Figure 29: Distribution of eigenvector centrality values for Ghana's organization-to-organization network.

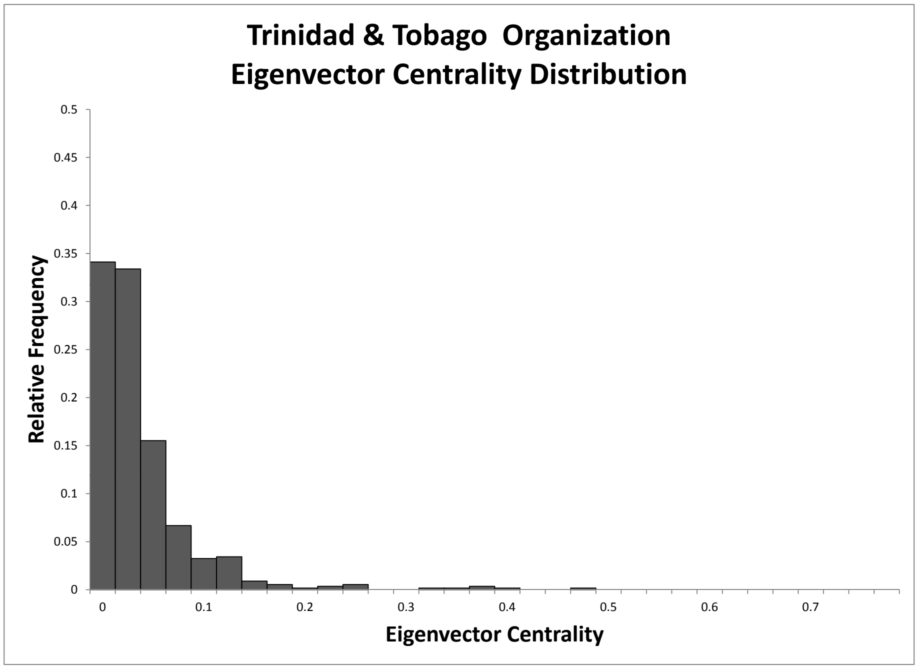


Figure 30: Distribution of eigenvector centrality values for Trinidad and Tobago's organization-to-organization network.

5.3 Prominent Organizations by Country

Tanzania Interestingly, Tanzania's most prominent organizations were quite different from the other networks. They included two professional associations, a brewery, an investment company, and a government ministry. The CEO Roundtable featured prominently in each metric, except for eigenvector centrality, occupying the top slot in degree and betweenness centrality and clique membership count. As its members represent the 55 top companies in Tanzania, the roundtable would logically serve as an information source for its members as well as a bridge to connect many disparate groups. The CEO roundtable was a member of 16 cliques and registered the second highest value for simmelian ties. Its mission is to promote economic growth through engagement with government and development organizations.

The Ministry of Finance and Economic Affairs registered the highest value for eigenvector centrality and simmelian ties and the second highest value for degree centrality and clique membership count. This government ministry manages the government's budget, financing, revenues, and expenditures. It also drafts tax and economic policies and financial regulations. Many of the individuals involved in the financial markets have been affiliated with this ministry.

Other prominent organizations included Tanzania Breweries Limited, the University of Dar es Salaam, National Investment Company Limited (NICOL), and the Confederation of Tanzania Industries (CTI), a business association that supports the manufacturing sector. Tanzania Breweries, a subsidiary of SABMiller, manufactures and distributes alcoholic and non-alcoholic beverages. The University of Dar es Salaam is the country's oldest and largest university with approximately 6,000 students. NICOL was purported to be Tanzania's

largest mutual fund prior to suffering extensive investment losses. NICOL's board was suspended in April 2011 and it was delisted from the Dar es Salaam stock exchange in July 2011 because it failed to submit 2009 and 2010 financial statements.

Ghana Four organizations figure prominently in Ghana's financial network. By far the most prominent is Ecobank Ghana Limited, which registered the highest values in each of the network measures. Furthermore, Ecobank's metrics were significantly higher than the most prominent organizations in each of the other networks. Ecobank Ghana is a subsidiary of Ecobank Group, a Pan African Banking organization with offices in 30 African countries. It provides comprehensive banking and financial services and operates 52 branches throughout the country. Another financial institution, CAL Bank Limited, occupied the number two position in all but one of the network measures. CAL Bank provides traditional and investment banking and asset management services.

The University of Ghana was the third most prominent organization when measured by degree and eigenvector centrality as well as clique membership count and simmelian ties. It was the second most prominent organization in terms of betweenness centrality. With almost 30,000 students, this oldest and largest university in Ghana has educated the vast majority of participants in the financial, industrial, and government sectors. Other prominent organizations included the Ghana Stock Exchange and State Insurance Company Limited, a 40% state-owned company with 25% of the traditional insurance market in Ghana.

Trinidad and Tobago ANSA McAL Limited, the University of the West Indies, the Institute of Chartered Accountants, and several financial institutions comprised the most prominent organizations in Trinidad. ANSA McAL is one of the largest conglomerates in Trinidad with almost $11 billion in assets and 6,000 employees. Its broad range of businesses includes manufacturing, transportation, financial services, real estate, automotive, and media. The company had the highest degree centrality, clique membership count, and simmelian ties. A close second in each of these metrics was the University of the West Indies, the oldest regional university in the Caribbean. The university has campuses in Trinidad, Barbados, and Jamaica and enrollment approximating 39,000.

Among the financial services companies that registered relatively high degree centrality and simmelian ties were Sagicor Financial Corporation and First Citizens Group. Sagicor provides life insurance and related investment products and services in Trinidad and several Caribbean countries. The First Citizens Group provides banking, asset management, brokerage, and advisory services in Trinidad, Barbados, and St. Lucia. The financial organizations that exhibited relatively high betweenness centrality were JMMB Group and Scotiabank Group. JMMB provides brokerage services, portfolio management, insurance, and loans to clients in Jamaica, Barbados, and Trinidad and Tobago. Scotiabank Trinidad and Tobago is part of Scotiabank Group, the Canadian international bank, and provides traditional retail and corporate banking services

5.4 Organization to Organization Network Centralization Metrics

Table 6 contains comparative network-level metrics for the three markets studied.

Table 6: Organization Network-Level Measures

Measure	Tanzania	Ghana	Trinidad and Tobago
Node Count	518	688	554
Link Count	938	1341	1135
Node Count (largest connected component)	323	471	379
Link Count (largest connected component)	790	1113	930
Average Distance	4.1784	4.3053	4.6561
Density	0.0070	0.0057	0.0074
Diameter	518	688	554
Diffusion	0.3878	0.4675	0.4664
Fragmentation	0.6099	0.5304	0.5308
Clustering Coefficient Watts-Strogatz	0.5281	0.6607	0.6360
Total Degree Centralization	0.0153	0.0360	0.0171
Betweenness Centralization	0.1133	0.1574	0.1849
Closeness Centralization (largest connected component)	0.247	0.258	0.274
Eigenvector Centralization	0.4351	0.6949	0.4476

All three organization networks exhibited low levels of closeness centralization suggesting that information flows are not centered around a few organizations. Consistent with the agent network analysis, total degree centralization was quite low for each organization network; however, Ghana's degree centralization was more than twice that of the other networks. Thus, Ghana has more highly central organizations in its network. Betweenness centralization is significantly higher in Trinidad - 63% greater than Tanzania and 17% higher than Ghana. This measure indicates that Trinidad has more intermediaries linking disconnected groups. In contrast, Ghana's eigenvector centralization value was 55% - 60% higher than the other networks, signifying that Ghana may have more strong organizations that are connected to other highly connected organizations.

In contrast to the agent-agent network metrics, Ghana's organization network exhibited the lowest density (0.0057), 18% lower than the other networks. Power may be more equally distributed among organizations in Ghana than in the other countries; however, all three networks' density levels were quite low. Thus, all three network topologies are more lattice than star shaped. Interestingly, Tanzania's diffusion measure was 16% lower than other networks indicating information may flow less easily throughout its network as the nodes are farther apart. Tanzania's network also exhibited a slightly shorter average distance (4.18 vs. 4.66 for Trinidad and 4.30 for Ghana) while its network had the lowest clustering coefficient (0.528), 20% to 25% lower than the other networks indicating less centralized information flows. Tanzania had the highest level of fragmentation (6.1 vs. 5.3 in the other networks) suggesting there are more disconnected nodes. Thus, Tanzania's organization network appears to be considerably different than the other networks - more fragmented, less clustered, and more diffused.

6 Limitations

The research team faced many challenges with data collection. Information availability varied widely among the entities examined. Some websites provided extensive biographies for their executives, while others listed very little or nothing at all. Some individuals may appear to be extremely influential relative to their peers because they have chosen to publish extensive background information. Conversely, influential individuals may prefer to remain anonymous posting little personal information on the internet. Consequently, the networks may contain structural holes if an undocumented relationship existed among individuals or organizations, due to either errors of omission or commission.

Also, many firms may not update their websites frequently, so researchers conducted additional assessments to validate individual résumé data. However, the network may still be incomplete if an individual has become a member of another board, completed a university degree, or joined a professional organization since his or her résumé was posted. Data collection is further complicated by the difficulty of keeping the dataset up to date. Short of developing a web crawler or checking corporate internet sites regularly, it is difficult to know when a key person changes institutions or a new individual joins a key organization. It is quite possible that by the time this research is completed, the network analysis will have lost a significant level of its accuracy in reflecting the capital markets. As a result, these static models are not very sensitive to changes among the economic actors and entities within the capital market.

Perhaps the greatest limitation in the network arises from a key assumption: if two people are associated with an organization or institution, they have a significant link or connection. In reality, this simplifying assumption causes the model to overstate some relationships. For example, the capital market network shows links between two people who went to the same university; however, universities are large organizations and student ages and fields of study vary such that two individuals attending the same university may never have met. Likewise, individuals may have worked for the same organization or served on boards of directors at different times making it difficult to know if an actual link exists between them. Furthermore, these models do not capture informal links among individuals and organizations. In developing countries, extensive forms of informal influence may be present. As a result of these limitations, our model may overstate the number of links among individuals and organizations or fail to recognize links that may exist. However, we believe this general approach can provide valuable insights into capital markets, and can be used as a model by researchers who seek to gain information by studying these markets from a network perspective.

7 Conclusions

This analytic approach, the innovative use of matrix algebra, and a unique methodology for real-world data collection provide major advances in the field of network science. As stated in the Limitations Section, it is difficult to determine how much data may be missing from this model, and it is equally difficult to keep the data current. Our team is confident that, with better and more accurate data, these analytic techniques have numerous applications on other sets of complex data as well.

In conclusion, our preliminary research generated functional networks and statistics for

three frontier capital markets. Quantitatively, the Trinidad and Tobago agent network is different than the networks of Ghana and Tanzania. The node level centrality metrics indicate that there are a small number of agents in the Trinidad network that have a greater amount of influence on this network than in the other two networks. There are also indications of a greater number of agents that bridge the gap between connected and unconnected nodes. Furthermore, key agents in the Ghana network may be more central than others and more agents may serve as bridges that attach disconnected groups. Finally, Tanzania's agent network has more leaders of strong cliques who are connected to other highly connected agents. These agents, at first glance, may not appear to be central to the network but may exert influence in nuanced ways.

A quantitative evaluation of the agent networks reveals that the Ghana network has a concentrated group of agents that rank high in prominence in the agent network descriptive metrics. In contrast, the Tanzania network has a very diverse group of prominent agents and the Trinidad network has several agents that are only prominent in selected centrality metrics. In Ghana, the concentrated group of prominent agents tend to be involved in numerous business, finance, and banking concerns and are graduates of the University of Ghana, In contrast, the most prominent agents in Tanzania have ties to industry associations, parastatal and state-owned organizations, and non-governmental organizations. In Trinidad, we see that prominent agents have ties to organizations in Jamaica and Barbados, have ties to the government, and are graduates of the University of the West Indies.

The organization networks of all three countries seem to follow a power-law distribution. An analysis of the organization networks also reveals that Trinidad's network is much different than the African networks. Trinidad's most prominent organizations seem to be more connected to other highly connected organizations. Organizations in Trinidad are affiliated with more distinct groups and may have stronger ties to the organizations with which they are linked. Our analysis also suggests that Tanzania's organizations are less connected than their counterparts in the other countries, while Ghana's most prominent organizations may exert more direct influence over the organizations with which they are linked.

Interestingly, the organizations that serve as information brokers in Ghana and Trinidad were both professional associations, but in Ghana, a major bank (Ecobank) performs this role. Furthermore, Ecobank's centrality measures were significantly higher than the most prominent organizations in the other networks. The major university in each country was central in each of their networks. In Trinidad and Tobago, a major conglomerate, ANSA McAL Limited, also featured prominently, as did the Institute of Chartered Accountants.

However, Tanzania's most prominent organizations were quite different than the other networks. They included two professional associations, a brewery, an investment company, and a government ministry. As the government in Tanzania was more robust before the IMF adjustments, many of its central actors remained connected in the economic, political, and government spheres after liberalization. In contrast, Ghana's pre-liberalization government was much weaker, which may account for the fact that associations and government ministries exert less influence in Ghana's financial system.

Future research will focus on refining the data collection process and conducting a functional analysis. We are also conducting a network analysis of an emerging market, the Czech Republic, to enable a vertical comparison. Such a comparison will reveal similarities and differences in the network structure of developing versus emerging markets furthering our understanding of the types of social networks that have fostered economic growth. Our

models will offer insights to economists seeking to understand the interconnections between economic actors and their affects on financial markets, risk, and economic conditions. This research will also provide governmental and nongovernmental organizations with a playbook when creating economic development policies enabling decision-makers to focus on aspects of the network that will generate results efficiently.

References

[Bor03] Stephen Borgatti. The key player problem. In *Dynamic Social Network Modeling and Analysis: workshop summary and papers*. National Academies Press, 2003.

[Bre09] Otto Bretscher. *Linear Algebra with Applications*. Pearson Prentice Hall, 4th edition, 2009.

[Fam70] Eugene F Fama. Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2):383–417, 1970.

[Fre79] Linton C. Freeman. Centrality in social networks: Conceptual clarification. *Social Networks*, 1(3):215–239, 1979.

[Goy07] Sanjeev Goyal. Introduction to connections: An introduction to the economics of networks. In *Connections: An Introduction to the Economics of Networks*, Introductory Chapters. Princeton University Press, 2007.

[Kir10] Alan Kirman. The economic crisis is a crisis for economic theory. *CESifo Economic Studies*, 56(4):498–535, December 2010.

[Kra98] D Krackhardt. *Simmelian Ties: Super Strong and Sticky*, pages 21–38. Sage, 1998.

[Lay06] David Lay. *Linear Algebra and its Applications (Third edition)*. Pearson, Addison Wesley, 2006.

[LSB11] Yang-Yu Liu, Jean-Jacques Slotine, and Albert-Laszlo Barabasi. Controllability of complex networks. *Nature*, 473(7346):167–173, May 2011.

[LZ96] Ross Levine and Sara Zervos. Stock market development and long-run growth. *World Bank Economic Review*, 10(2):323–39, May 1996.

[MJ11] Ian McCulloh and Anthony Johnson. Advanced network analysis and targeting course, 2011. Preprint: http://www.dean.usma.edu/departments/math/courses/ma488a/ANAT%20Course%20Guide.pdf, Accessed 10-27-2011.

[ORA] ORA. http://www.casos.cs.cmu.edu/projects/ora/, Accessed 10-05-2011.

[SG11] Joseph E Stiglitz and Mauro Gallegati. Heterogeneous interacting agent models for understanding monetary economies. *Eastern Economic Journal*, 37(1):6–12, 2011.

[Str88] Gilbert Strang. *Linear Algebra and Its Applications*. Brooks Cole, February 1988.

[WF94] Stanley Wasserman and Katherine Faust. *Social Network Analysis: Methods and Applications*. Number 8 in Structural analysis in the social sciences. Cambridge University Press, 1st edition, 1994.

[WS98] D. J. Watts and S. H. Strogatz. Collective dynamics of 'small-world' networks. *Nature*, 393(6684):440–442, June 1998.

8 Appendix A - Top Organizations in Various Centrality Measures

Table 7: Top Organizations in various centrality measures

	Tanzania		**Ghana**		**Trinidad & Tobago**	
Metric	Agent	Value	Agent	Value	Agent	Value
Total Degree Centrality	CEO Roundtable	0.016	Ecobank	0.038	ANSA McAL Limited	0.019
	Ministry of Finance & Economic Affairs	0.012	CAL Bank Limited	0.025	University of the West Indies	0.018
	Tanzania Breweries Limited	0.01	University of Ghana	0.024	Sagicor Financial Corporation	0.015
	Confederation of Tanzanian Industries	0.01			First Citizens Group	0.013
Closeness Centrality (largest connected component)	CEO Roundtable	0.370	Ecobank	0.366	Institute of Chartered Accountants	0.358
	NICOL	0.364	Ghana Bar Association	0.336	University of the West Indies	0.332
	Tanzania Breweries Limited	0.353	Ghana Stock Exchange	0.331	Ernst & Young	0.313
	PricewaterhouseCoopers	0.346	University of Ghana	0.320	Scotiabank Group	0.311
	Tanzania Investment Bank Limited	0.344	Merchant Bank Ghana Ltd	0.319	Trinidad & Tobago Stock Exchange	0.311
Betweenness Centrality	CEO Roundtable	0.115	Ecobank	0.159	Institute of Chartered Accountants	0.188
	Tanzania Breweries Limited	0.066	University of Ghana	0.101	University of the West Indies	0.126
	University of Dar es Salaam	0.065	CAL Bank Limited	0.082	JMMB Group	0.068
	National Investment Company Limited	0.059	State Insurance Company Limited	0.075	Scotiabank Group	0.063
Eigenvector Centrality	Ministry of Finance & Economic Affairs	0.455	Ecobank	0.716	Institute of Chartered Accountants	0.475
	Tanzania Breweries Limited	0.419	CAL Bank Limited	0.472	ANSA McAL Limited	0.372
	National Investment Company Limited	0.4	Ghana Stock Exchange	0.355	Sagicor Financial Corporation	0.371
	Confederation of Tanzanian Industries	0.399				
Clique Membership Count	CEO Roundtable	16	Ecobank	21	ANSA McAL Limited	14
	Ministry of Finance & Economic Affairs	14	CAL Bank Limited	17	University of the West Indies	14
	Confederation of Tanzanian Industries	10	University of Ghana	13	Institute of Chartered Accountants	13
	National Investment Company Limited	10	Ghana Stock Exchange	12	Central Bank of Trinidad and Tobago	12
			State Insurance Company Limited	12		

	Tanzania		Ghana		Trinidad & Tobago	
Metric	Agent	Value	Agent	Value	Agent	Value
Simmelian Ties	Ministry of Finance & Economic Affairs	0.058	Ecobank	0.102	ANSA McAL Limited	0.067
	CEO Roundtable	0.054	CAL Bank Limited	0.066	University of the West Indies	0.051
	Tanzania Breweries Limited	0.052	University of Ghana	0.044	Sagicor Financial Corporation	0.047
	Government of Tanzania	0.05	State Insurance Company Limited	0.042	First Citizens Group	0.043